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A DIAGNOSTIC MODEL FOR ADHD WITH WLD IN STUDENTS USING HEALTHCARE ANALYTICS

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Approval of Thesis

The undersigned certify that they have read the thesis entitled

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Submitted by

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In partial fulfillment of the requirements for the degree of

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Dedication

I dedicate this work to my family; the greatest source of support and inspiration. I hope this work sparks the wheels of change for their future.

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First and foremost, I would like to thank my husband, Daniel, for pushing me to continue this work when I did not feel like I could. His patience, love, feedback and support got me to combat all the “This will not work” with “Here is how it will work”. His coaching and endless help with our children has helped me focus on all the hours I needed to make this happen.

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Abstract

Previous research has shown students that have Attention Deficit Hyperactivity Disorder (ADHD), a mental health disorder that displays excessive inattentive, impulsive, and hyperactive behavioural symptoms, have an increased risk of having Written Language Disorder (WLD), a learning disorder that displays written composition issues (multiple spelling, grammar and punctuation mistakes, sentences that lack cohesion and topic flow, and written assignment completion). The prevalence of WLD without ADHD or another mental health disorder is quite rare. To measure the prevalence of ADHD and WLD in a student, this research created a computational 'artificial neural network (ANN)' model that combined the outcomes of common screening tools for ADHD with written performance tasks as a measure for WLD. A study based on this ANN shows that ADHD students have a high prevalence of WLD in comparison to typical (non-ADHD or control) students, demonstrating the link between ADHD and WLD.

Keywords: Attention Deficit Hyperactivity Disorder, Written Language Disorder, ADHD, WLD, healthcare analytics, behavioural and learning disorder analysis

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Chapter 1. Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is a mental health disorder that usually appears in school age children, affecting 1 in 10 in the United States (Visser, Zablotsky, Holbrook, Danielson, & Bitsko, 2015). Students with the disorder are inattentive (have difficulty focusing on a task for a long period of time), overly impulsive (act without thinking), and/or hyperactive (moving excessively, often at inappropriate times) (Mayo Clinic, 2018). This disorder is diagnosed primarily when the child is of 7 years of age, and even with treatment, the disorder continues to be present in the child's adult life, affecting their social and learning behavior, including their post-secondary years (Casa, Ferrer, & Fortea, 2011).

Because adult ADHD symptoms can mimic those of other mental health disorders, such as anxiety (moving excessively, feeling overwhelmed) and depression (difficulty concentrating and frustration), it is challenging to diagnose the disorder in adults by the key traits mentioned above. Instead, medical professionals turn to the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) for the ADHD diagnosis in adults. The DSM is published by the American Psychiatric Association and it offers a baseline definition of ADHD, which states:

"[The student] must have six or more signs and symptoms (five for students over 17) from one or both of the two categories below.

Inattention

- Often fails to give close attention to details or makes careless mistakes in work or other activities
- Often has difficulty sustaining attention in tasks

- Often does not seem to listen when spoken to directly
- Often does not follow through on instructions and fails to finish tasks
- Often has difficulty organizing tasks and activities
- Often avoids, dislikes or is reluctant to engage in tasks that require sustained mental effort
- Often loses items necessary for tasks or activities
- Is often easily distracted
- Is often forgetful in daily activities

Hyperactivity and impulsivity

- Often fidgets with hands or feet or squirms in seat
- Often leaves the room when remaining seated is expected
- Often is physically active or restless in situations when it's inappropriate
- Often has difficulty quietly engaging in leisure activities
- Is often "on the go" or often acts as if "driven by a motor"
- Often talks too much
- Often blurts out answers before questions are completed
- Often has difficulty awaiting turn
- Often interrupts or intrudes on others' conversations

In addition to having at least five symptoms from these categories, someone with adult ADHD must have had:

- inattentive or hyperactive-impulsive signs and symptoms that caused impairment and were present as a child

- behaviors that were not normal for children the same age who did not have ADHD
- symptoms for at least six months
- symptoms in more than one setting that significantly impair performance at school or work or negatively impact home life or relationships
- ADHD symptoms that occurred exclusively during the course of schizophrenia or another psychotic disorder and must not have been be better explained by another mental disorder, such as depressive or bipolar, anxiety, dissociative, or personal disorder, substance intoxication or withdrawal." (American Psychiatric Association, 2013)

Lastly, there are three types of ADHD that can be presented in the student. They are:

Combined presentation – all three core features are present, and ADHD is diagnosed when ≥6 symptoms of hyperactivity/impulsivity and ≥6 symptoms of inattention have been observed for ≥6 months

Predominantly inattentive presentation – diagnosed if ≥6 symptoms of inattention (but <6 symptoms of hyperactivity/impulsivity) have persisted for ≥6 months

Predominantly hyperactive/impulsive presentation – diagnosed if ≥6 symptoms of hyperactivity/impulsivity (but <6 symptoms of inattention) have been present for ≥6 months.

The spectrums of severity of diagnosed ADHD are as follows:

Mild – few, if any, symptoms in excess of those required to make the diagnosis are present, and symptoms result in no more than minor impairments in social or occupational functioning

Moderate – symptoms or functional impairment between ‘mild’ and ‘severe’ are present

Severe – many symptoms in excess of those required to make the diagnosis, or several symptoms that are particularly severe, are present; or the symptoms result in marked impairment in social or occupational functioning.

With such comprehensive diagnostic criteria, it would seem that the diagnosis for ADHD would be an easy one to make. But not quite. The ADHD diagnosis in adults is difficult because the screening tests are limited in matching the criteria (Hamed, Kauer, & Stevens, 2015). For this reason, additional information was sought by researchers to confirm ADHD in adults (Schoechilin & Engel, 2005). In this context, in the last twenty years, psychologists and educators have begun to recognize a learning disorder known as “written language disorder” or WLD (classified as a “specific learning disorder” in the DSM-V) occurring in students (Katusic, Colligan, Weaver, & Barbaresi, 2009). This disorder is commonly associated with ADHD or autism mental health disorders (Yoshimasu, et al., 2011) (Re & Cornoldi, 2010) (Rodríguez, et al., 2015), and very rarely WLD occur as a learning disability without an associated mental health disorder. The disorder is also usually diagnosed when the child is 7 years of age and the symptoms follow well into the student’s adulthood.

The symptoms of the WLD according to the DSM-V are evidenced in impairment of:

- Spelling accuracy
- Grammar and punctuation accuracy
- Clarity or organization of written expression

[with] the [WLD] impairment lasting longer than 6 months despite having targeted help, and with [the student] being prone to Dysgraphia; a condition that describes the difficulties with handwriting (American Psychiatric Association, 2013).

Previous research indicates there is a link between ADHD and WLD. A study conducted at the Mayo Clinic in Rochester, Minnesota, showed that ADHD students had a weakness of working (short-term) memory, and concluded that the composition skills were not learned at the moment they were taught (Yoshimasu, et al., 2011). In fact, in that study of the 379 students that had been diagnosed with ADHD, more than 50% of the also had writing difficulties for this reason. In another study from the Universidad de Valencia in Spain, students with ADHD were found to lack the attention to detail required for writing letters legibly by hand (Casa, Ferrer, & Fortea, 2011). In this study, ADHD writers were on average 35% less proficient than typical writers; and in a study from the University of Padova, Italy, ADHD students wrote rather quickly to get their ideas on paper, in turn sacrificing legibility and composition quality (Re & Cornoldi, 2010). In this study, ADHD writers were on average 25% less proficient than typical writers.

Statement of Problem

While the previous studies mentioned above indicates the link between the disorders, measuring that link is not as easy. There are two major problems in getting that measurement and diagnosis. Mental health disorders and learning disabilities are not readily diagnosable as they revolve around behavioral and learning performance symptoms that are less deterministic unlike physical symptoms that are more factual. This means that with many sources of testing, the process to get a diagnosis is a lengthy one (MyHealth Alberta, 2019), physical questionnaires (MyHealth Alberta, 2019), academic performance testing (McConaughy, Ivanova, Antshel, & Eiraldi, 2009), and in some cases, neural scans (Lenartowicz & Loo, 2014). It is important to note that since neural scans are expensive and are based on prior referral for other neurological disorders, they are rarely used for standard testing, and the results are mainly gathered for research. The sources for the testing also come from different avenues, such as information from general practitioners, psychologists, counsellors, teachers, pediatric psychiatrists, speech pathologists, and neurologists. With these different sources, the onus is on the parent of the student or adult student to pursue this information, even when they may not have knowledge of the information they need to pursue. And, though it is the psychologist or psychiatrist that makes the eventual diagnosis, gathering the information from all these sources can take 2 to 3 years, while the student remains undiagnosed, struggling to get through the academic years and falling further and further behind in their studies.

To combat these problems, this research posits the use of a computer-based mental health and learning performance diagnostic model to assist in the gathering and analyzing of information needed for measurements and a reliable diagnosis. The tool uses physical, behavioural and performance data sets from the student that are interoperable and algorithms that are aware of each other’s outcomes. This allows the medical professional to have a more refined set of information to assist them with a quicker diagnosis.

The datasets will be from students that have been formally diagnosed with ADHD (ADHD group) and students that have not been formally diagnosed with ADHD (control group) as a comparison. The ADHD diagnosis that is being considered for the ADHD group will be the combined type (that is, the students that have been formally diagnosed have both attention and hyperactivity issues), in the moderate to severe spectrum, as that is more common in the previous studies.

To gain clarity in exposing the link and its measurements, this research reviews the methodology from the literature pertaining to contemporary diagnoses for ADHD and WLD, to reveal techniques 1) to interoperate ADHD and WLD data sets, and 2) to explicitly associate the ADHD and WLD diagnostic methods. The results are then validated in a study that employs a novel computational technique that addresses the two aforementioned goals.

Research Question

Given that extensive research exists that determine the diagnostic criteria for ADHD and WLD, and that both disorders have tests that can collect preliminary measurements, the research question of this thesis is construed as follows:

Is there a computational model that can identify and integrate measurable factors that contribute to ADHD and WLD diagnosis to produce a more accurate diagnostic outcome?

A software system called the Mental Health Analysis & Diagnostic Service (MHADS) has been developed to address this research question. MHADS first takes information from a questionnaire on physical symptoms, behavioural rating scales and performance tests to determine a student's diagnosis on ADHD and WLD. The test outcomes are then integrated through a neural network to yield measurements on diagnosis that are significantly more accurate than individual tests. This analysis will thereby create a diagnostic model that will assist medical professionals in determining the likelihood that a student has a mental health and/or learning disorder, and the likelihood that the disorder is ADHD with WLD.

Thesis Organization

This thesis is organized into five chapters. The first, this one, is an introduction to the topic. It briefly provides an overview of the problem and a research question.

The second chapter provides an in-depth review of the literature pertaining to ADHD and WLD and the analysis techniques to measure the degree of affliction of ADHD and WLD.

The third chapter explains the methodology in detail, including an overview of the underlying technology and details of the study procedure.

The fourth chapter shows the result of the methodology, including outcomes arising from previous studies, and the equations and tools used to produce those outcomes.

The fifth chapter summarizes the author's conclusions based on the analysis, focusing on implications of the study, and gives recommendations regarding the pedagogical importance of the outcomes. The section also identifies potential future research as extensions of the current work.

Chapter 2. Review of the Literature

Common Screening Tests for ADHD

While there have not been many studies pertaining to machine learning for adult ADHD, literature reports analysis of patient datasets obtained through screening tests for adult ADHD. These screening tests can be in the form of rating scales and performance tests that offer general diagnosis, or in the form of brain imaging patterns that measure severity of ADHD for research purposes. A literature review was performed to extract common features of these screening tests.

Behavioural Questionnaire and Self-Reporting Testing

Before a consultation with a psychologist, psychologists, and/or teachers, the patient starts with a self-reporting behavioural questionnaire or scale to assess if they have ADHD symptoms. Examples of self-reporting scales and behavioural questionnaires are the Adult Self-Reporting Scale for ADHD (ASRS) (CADDRA, 2014), Behavior Assessment System for Children (BASC) (Pearson, 2019), Vanderbilt ADHD Diagnostic Rating Scale (VADRS) (Wolraich, et al., 2003), and the Conners Comprehensive Behavior Rating Scales™ (Conners CBRS™). All scales and questionnaires have several questions that are rated and weighted depending on the patient’s answer to if the weighted answer matches the term in the ADHD classifier (i.e. indicates they have ADHD).

Such a scale was used in a demographics meta-analysis. Using MEDLINE, Psyclit and EMBASE as its source demography data, the meta-analysis (Simon, Czobor, Bálint, Mészáros, & Bitter, 2009) investigated the prevalence (or the commonness) of adult ADHD. The resulting dataset consisted of sample size, mean age, age range, and gender, along with the ADHD Adult Self-Reporting scale for correlates to the characteristics in the DSM-IV classifier for ADHD. The results that showed high rates in hyperactivity, inattention and impulsiveness categories according to the DSM-IV, which were in turn validated against the same DSM-IV classifier (Appendix A - Figure 1), indicating the correlated dataset was considered a screening tool for ADHD. However, the prevalence and covariates were only as sensitive and specific as the rating scale used. Without performance testing and physical screening, the rates were subject to other disorders that could have the same behavioural characteristics (oppositional defiance disorder, autism, etc.).

Reaction-Based Performance Testing

To track the impulsiveness, hyperactivity, or inattentiveness symptoms in a patient, reaction-based performance testing can be used. Examples of this kind of testing are go-no go/stop-start tasks, such as Conners' Continuous Performance Test (CPT) 3, Test of Variable Attention (TOVA), and Integrated Visual and Auditory Continuous Performance Test (IVA CPT).

A variety of these tests were analyzed as part of a meta-analysis (Schoechilin & Engel, 2005) on 50 empirical studies that exclusively used performance tests on tasks such as reading, sorting, and picture completion. A dataset was created based on age, sample size, gender, years of education and IQ for ADHD and control patients. The dataset was then filtered by performance test and ability of the patient in each test, with the results demonstrating areas of weakness in patients' performance. The areas were then compared against control group performances, creating baseline scores and performance domain definitions for ADHD patients in verbal memory, sustained attention, and other such features as noted in the pool effect sizes and parameters in Appendix A - Figure 2 below. Negative *d'* values indicated lower performance in the ADHD group for the different features (functional domains) with the baseline being 0. As an extension of this meta-analysis, one can conceive a causal model that establishes relationships between test indicators and their respective baseline scores. Such a model can serve as an ADHD classifier. Further, the probabilities associated with relationships between test indicators can be machine learned to predict the severity of ADHD. Such machine learning solutions can determine the confidence level of a feature to ADHD diagnosis.

While the meta-analysis focused on performance testing as the screening method for ADHD, it neglected other screening tools that would improve the accuracy of the performance test datasets. Other screening tools such as the physical questionnaires or the behavioural rating scales could rule out factors that contribute to weakness in performance test data. For instance, a remarkably lower levels of performance of a patient in a performance test can be confounded by pre-existing conditions such as head trauma or anxiety as covariates. Thus, one can conclude that while a single screen offers valuable information on the thresholds of ADHD diagnosis, the confidence level of that single screen can be quite low.

Another review (Kofler, et al., 2013) studied the delayed reaction times (RT) of ADHD patients used Medline, PubMed, PsycInfo, PsycArticles, PsycBooks, ERIC, Dissertation Abstracts International, and the Social Science Citation Index for symptom (keyword) searches. Search terms included permutations of the ADHD diagnostic label (ADHD, ADD, attention deficit, attention problems, inattent*, hyperact*, hyperkinesis, minimal brain dysfunction/damage, MBD), variability, reaction time (RT), variability metrics (SDRT, coefficient of variation, CV, sigma, tau, RT of SE, Slow-*, frequency, signal processing), and tasks (scales and tests) frequently used to derive RT variability data (TOVA, Conners' CPT, stop signal, reaction time, motor speed, SRT, CRT, n-back, CPT, Flanker, Stroop, go/no-go, vigilance, inhibition, attention, KITAP, Attention Network Test, ANT). After discarding child-related ADHD studies and retaining only adult-related ADHD studies, the authors used means, standard deviations (SDs), and sample sizes of reaction times for each group to compute Hedges' g effect sizes (i.e. the strength of reaction times in relation to searched ADHD attributes in the studies). Commonalities on reaction time patterns created a model based on reaction time evaluation in screening ADHD. While this study demonstrated the link between reaction times and ADHD, the performance testing associated with RT was a snapshot of the patients overall mental performance. Also, the tests were sometimes a one-time test with no re-testing. Recording a history of performance with pre-screens for physical factors that would affect the reaction time would have strengthened the meta-analysis results.

Brain Imaging

There have been numerous studies on behavioural disorders linked to brain patterns discovered through scans or imaging. Examples of scans and imaging used for discovering these patterns are Magnetic Resonance Imaging (MRI), Positron emission tomography (PET) scans, and electroencephalogram (EEG) tests.

Imaging was used in a meta-analysis (Cortese, et al., 2012) that synthesized 55 fMRI (functional magnetic resonance imaging) studies using PubMed, Ovid, EMBASE, Web of Science, ERIC, CINAHAL, and NeuroSynth databases. The meta-analysis had

16 adult ADHD studies (the other studies 39 studies being on childhood ADHD). The adult ADHD studies reviewed the brain pattern activity of adult ADHD patients in comparison with normal adult brain pattern activity. A cluster analysis on brain patterns from comorbidity factors (e.g., psychiatric recommendations, presence of other mental disorders and external stimulants) indicated that the brain pattern activity from the fMRI in the 16 studies was an effect of these factors. A diffusion model was then created from the analysis to demonstrate other regions of interest (ROIs) that were affected from ADHD, aside from the most commonly known prefrontal-striatal area of the brain--where normal neurotransmitter activity for the working memory (activity that would be decreased in ADHD patients) would reside. Adults with ADHD showed significant hypoactivation relative to comparisons in the right central sulcus/precentral gyrus and middle frontal gyrus, indicating less than normal activity in these areas as well. While the meta-analysis focused on studies that viewed ROIs in the brain for less than normal activity (i.e. regions that suggest ADHD symptoms), performance testing would have confirmed the areas of activity that were being mapped. For instance, anxiety could have impacted the same activation areas as hyperactivity. Tracking the performance data of participants in conjunction with the areas of fMRI brain pattern activity would have narrowed down the cause of the brain pattern activity. It also important to note here that while brain imaging has been used extensively in research, it is because of comorbidity factors (a factor that goes along with the ADHD’s regions of interest in the brain) that ADHD regions have become relevant. Brain imaging is very expensive and does not provide trusted results for ADHD (Watson, 2016). Therefore, it is not a common practice

when diagnosing ADHD, and fMRI data will not be used as a screening test in this research.

A pilot study (Robeva, Penberthy, Loboschefski, Cox, & Kovatchev, 2004) using Bayesian networks for refining the probability of ADHD in 6 college females and 6 matched controls (using rating scales and EEG performance testing) found that the probability of a participant having ADHD was 76% for the ADHD group and 8% for the normal or “typical” group. The study used the DSM classifier for the rating scales and matched a typical sample as the standard against the EEG performance testing, Alpha Blockade Index (ABI). This study comes close to combining multiple screening models. However, its low sample size not only makes it suspect under a specificity-sensitivity validation, the lack of repeated performance testing does not create a strong case for the use of a Bayesian network.

The supplemental review employed the systematic review method and identified 15 more studies (in addition to the 5 studies above) published in PubMed, EMBASE and ResearchGate. A meta-analysis was then conducted (Mitchnick, Kumar, Kinshuk, & Fraser, 2016) on these 15 extra studies to determine the effectiveness of a single screening method’s relationship with the DSM classifier as opposed to the relationship of a combined screening method with the DSM classifier. The review gathered an average sample size of at least 60 participants, aged between 18-30 years, exhibiting primary adult ADHD symptoms. Variables collected from the meta-analysis include mean age, method of screening: brain size and development through Magnetic Resonance Imaging (MRI) scans, reports of hyperactivity, inattentiveness and impulsiveness history through rating scales (such as the ones described in the Behavioural and Rating Scale section above), reports of fatigue and signal response time through performance testing, and the administration location of the test: general practitioner's office, psychologist's/psychiatrist's practice, imaging centre, etc. The studies were grouped by occurrences (i.e. how often they are used in the 20 studies surveyed) and the match with DSM-V, respectively (see Table 1).

Table 1

The average strength of the relationship between the studies' screening test data and the ADHD DSM-V classifier

Screening Test	Number of Studies*	Relationship with DSM (Avg Correlation Coefficient r)
ASRS Scale	10	0.72
MRI/PET	2	0.80
Reaction-Based CPT	4	0.66
ASRS, MRI, CPT	4	0.90

***Note:** Data for these studies are compiled from Mitchnick, D., Kumar, V., Kinshuk, & Fraser, S. (2016).

The mean age was 30 years with a mean sample size of 75 patients. The ANCOVA tests validated the relationship between the variables for inattentiveness and hyperactivity and the DSM-V classifier for adult ADHD (this is assuming the correlation coefficient was not already been determined in the study). If the correlation coefficient showed a strong relationship (r = <0.80) between the participant results and the diagnostic terms, the closer the model (or combination of models) was to the actual classification (Mitchnick, Kumar, Kinshuk, & Fraser, 2016).

Written Performance Testing

In the past 20 years, there has been research into identifying behavioural disorders in students that have learning difficulties (and learning difficulties in students that have behavioural disorders). Testing for this kind of research can come in the form of written composition testing, handwriting tests, and IQ testing.

For written composition testing, Woodcock-Johnson (WJ) tests (Woodcock, Shrank, McGrew, & Mather, 2007) were designed to identify students with special needs. A literature review explored the use of WJ tests to diagnose ADHD, particularly in using its ‘Report Writer’ test to track behavioural attributes of ADHD (Abu-Hamour, Al Hmouz, Mattar, & Muhaidat, 2012). The literature review reviewed concepts such as cognitive efficiency, processing speed, short-term memory and long-term retrievals. These concepts are derived from articles published by Schrank (Schrank, 2005) and McQuade (McQuade, et al., 2011). The review indicated that these concepts were linked to ‘attention’ deficiency in ADHD patients. In the literature review, a cluster analysis was done on the spelling, writing fluency, writing content, and editing from the ADHD group’s writing samples, in conjunction with the concepts, defining the links. The two studies (Schrank and McQuade) in the review found that concepts were all scored low and academic fluency overall was low as well.

This last study and the deficiencies identified in earlier studies inspired this thesis. The last study did not offer a fixed set of writing factors that could be used as a measure for the ADHD diagnosis, but it did offer a good start to define a standard scale based on the writing performances of ADHD students. This study also inspired a follow up literature review on writing performance and its relation to ADHD. This additional review, discussed below, yielded the identification of more definitive writing-related measures for ADHD diagnosis. Further, this additional review also offered guidelines for combining screening methods to rule out confounders arising from other behavioural disorders that might affect the writing performance.

Methods for Measuring Writing Difficulties in ADHD Students

While the first-of-its-kind systematic review (Mitchnick, Kumar, Kinshuk, & Fraser, 2016) was accomplished to determine contemporary methods used for screening ADHD, another systematic review was required to determine the set of factors in student writing that could be linked to the ADHD diagnosis. This proved to be a challenge though as at the time of this review, there were not much research that explored adults with ADHD and writing difficulties. However, a more comprehensive literature review on children's studies helped determine a set of written performance variables to measure against the DSM classifier for ADHD and WLD, which is highlighted in the Table 2 below.

A study (Casa, Ferrer, & Fortea, 2011) at the University of Valencia investigated the presence of written expression difficulties among students who were already diagnosed with ADHD. The participants of the study were administered neurological assessments, physical assessments and the Conner's rating scale with T-scores > 65 (T-scores greater than 60 indicating moderate to severe on the spectrum). The study used variables that traditionally have been used in rating narrative discourse. More specifically, the study used measures/variables that have been used in the expression, reception and recall of a narrative instrument named the "Expression, Reception and Recall of Narrative Instrument (ERRNI)" (Bishop, 2004).

The variables used in the study (Casa, Ferrer, & Fortea, 2011) included the planning process of writing:

- structure (introduction, body, etc.),
- time sequence errors (events out of chronological order),
- content errors (statements not on topic),
- cohesive adequacy (number of incomplete references), and
- connective cohesion (number of connectors that established different relationships—like “since” or “because”).

The variables also measured the translation (or evaluation) process of writing:

- number of words,
- number of sentences,
- mean length of utterance in words (dividing the number of mean words by the number of sounds of a word—common in the Spanish language),
- syntactic complex index (number of subordinate clauses and compound verbs divided by the total number of utterances),
- morphosyntactic errors (he/she, past/present tense misuse), and
- type-token ratio corrected (number of words related to the topic (tokens) divided by number of different topic words (types).

The variables also considered revisions that included:

- formal revisions (punctuation and spelling corrections),
- content revisions (shifting, deleting, and adding content),
- uncorrected formal errors (subtraction of formal revisions from formal errors), and

- uncorrected content errors (subtraction of content revisions from content errors).

ANCOVA tests were used to compare writing expression difficulties between students with ADHD and students without ADHD. However, the attributes of WLD were not matched against the outcomes of the study, since the focus of the study was about highlighting written difficulties in general.

The University of Valencia study (Casa, Ferrer, & Fortea, 2011) was the most thorough of all the studies reviewed for ADHD measures, and provided a more accurate contrast between the ADHD group and the typical group. However, the results are still speculative since standards do not exist yet that link the above-mentioned written performance variables specifically to attention deficiency or hyperactivity. More research is needed to determine, strengthen and validate the links between written performance measures with the unique attributes of the ADHD diagnosis.

Another study (Re, Mirandola, Esposito, & Capodieci, 2014) at the University of Pedova explored the prevalence of spelling errors among the written compositions of students diagnosed with ADHD. This study concluded that spelling was linked to the phonological working memory of the student. Here, two sets of written tasks were administered to 19 ADHD students and 19 “normal” or typical students. All the students were 10-year-old males. The ADHD students were screened using teacher interviews and the Italian equivalent of ADHD Self-Reporting Scale--ASRS (Kessler, et al., 2005) (SDAI - Scala di disattenzione e iperattività). The first task was a diction exercise, where phonetic words (words that would sound differently from how they are spelled— e.g., “phone” vs. “fone”) were read aloud. The second task was also a diction exercise, but with words that sound the same as they are spelled (e.g., “mat”). Using ANOVA, the number of spelling errors (phonological and nonphonological) observed in the ADHD group was compared against the number of errors in the control group. Further, sequence errors (words written in the wrong order), number of words, number of sentences, and morphosyntactic (accents missing on letters) errors were also observed between the two groups. The results concluded that the phonological working memory performance of the ADHD students was 10% lower than that of the typical group, and that the ADHD group was more prone to spelling, sequence, and morphosyntactic errors.

Re, Mirandola, Esposito, and Capodieci recognized that they were focusing on a very specific part of written expression and acknowledged that their conclusions could be substantiated from a third task that collected performance data not related to working memory (Re, Mirandola, Esposito, & Capodieci, 2014). Focusing on whether the written composition (specifically, the discourse level that demonstrates cohesion adequacy) aspect of the performance task contributes to the working memory would be beneficial in strengthening the relationship between their findings and the WLD diagnosis.

Another pilot study (Reid & Lienemann, 2006) at the University of Nebraska analyzed the writing exercises of elementary students who had been diagnosed with ADHD and students who had difficulty in their writing performance. The diagnosis originally was based on rating scales and parent interview. However, a Test of Written Language (TOWL-3) (Hammill & Larsen, 1996) was administered after these two screens (that is, ADHD diagnosis and difficulty in writing performance) to measure writing difficulty. This third screen identified writing difficulty measures such as time spent writing, number of essay elements (introduction, body, etc.), number of words, transition words (words that change the sentence topic) and quality ratings (strength of argument, which was a rating given by a teacher's review). The study found that focusing only on these measures, the teachers could use a Self-Regulated Strategy Development (SRSD) model to assist ADHD students in their writing. The results of the SRSD model (probe effects during each of the new writing tasks the students completed) showed that ADHD students' writing performance vastly improved in specific areas, such as topic consistency, word count (longer content) and composition quality (spelling and grammar error reduction and increased vocabulary).

Reid's study (Reid & Lienemann, 2006) showcases the need to create a definitive writing performance measure to diagnose ADHD rather than using measures observed from unrelated datasets. While the study had a small sample size (4 students), the combination of the writing performance test with the rating scales and behavioural interviews yielded significant differences in results from a typical (i.e. without ADHD) student, substantiating the argument to use writing performance tasks as a screening tool in combination with other screening tools for ADHD diagnosis. Further, a writing performance screen is more beneficial to the validity of the diagnosis as it strengthens relationships arising from other ADHD screens. The model used in this thesis uses a Test of Written Language (TOWL) (Hammill & Larsen, 1996) based method for measuring and linking the areas of writing difficulty to target attributes in ADHD diagnosis.

Based on the literature reviewed, a comparison table (Table 2) (Mitchnick, et al., 2017) was created that identified factors one could use to measure the writing performance of students afflicted with ADHD. Comparing this list with the attributes of WLD, the list of factors offered a more definitive set of measures that associated WLD with ADHD (which is explained more in the data collection in the exact measures collected). Other behavioral disorders that might affect written performance will be ruled out with pre-screens of cognitive concepts mentioned in the data collection section as well and combining the outcomes of different screening tools enables the inclusion of physical or behavioral factors (symptoms).

Table 2

Variables used for Measuring of Writing Difficulties for ADHD students in a Systematic Review

Writing Variables	Casa, Ferrer, & Fortea (2011)	Capodieci, Esposito, Mirandola, & Re (2014)	Lienemann & Reid (2006)	Schanks (2005)	McQuade (2010)
Errors					
Formal (spelling) errors	X	X	X	X	X
Content (grammatical) errors	X			X	X
Morphosyntactic errors	X	X			
Time sequence errors	X	X	X		
Uncorrected formal errors	X	X	X	X	X
Uncorrected content errors	X			X	X
Corrections					

Formal (spelling) revisions	X				
Content (grammatical) revisions	X			X	X
Type-token ratio corrected	X			X	X
Numbers					
Number of words	X	X	X		
Number of sentences	X	X			
Mean length of utterance in words	X				
Pairing					
Syntactic complex index	X				
(Cohesive Cohesion) Structure	X		X	X	X
Cohesive adequacy	X		X	X	X

Each study reported from the literature so far used a single screening tool on unique patient dataset for analysis. None of them used a combination of the most common screening tools for their analysis. Doing so would have allowed for the inclusion of factors (symptoms) found in the other screening tests to explain away confounding factors.

However, out of the table above, a profile can be created for the ADHD student that has writing difficulties based on the frequency of metrics analyzed in the literature:

Profile for ADHD Student with Writing Difficulties:

- Number of words
- Number of Sentences
- Number of spelling errors overall (and corrected)
- Number of grammatical errors overall (and corrected)
- Morphosyntactic Errors (looks for consistent pronouns in the sentence (ex. "he" in previous sentence, against "he" in next sentence), and any inconsistent use of past/present/future tense (ex. “was” with “is” in the adjacent sentence))
- Time sequence errors (if "third" comes before "second", capitalization in the first word, ending punctuation in the last word, adverb after verb, etc.)
- Connective Cohesion (number of sentences paired together based on relationship) - synonyms and connectors for connectivity
- Cohesive Adequacy (number of incomplete sentences) - Check for verb ending a sentence ("was."). Check for incomplete ties
(Mitchnick, et al., 2017)

Not only are these metrics in the profile found in ADHD students, but they can be used to identify WLD as well (which is explained of how the metric is measured in the “Data Collection” part of the Methodology section)

To analysis these metrics for WLD symptoms, writing analytics will need to be applied to the ADHD student’s writing. The next section describes some tools that are used to identify and apply those analytics.

Writing Analytics

Analytics is the real-time analysis (or studied separation) of data (Cooper, 2012). Analytics are usually quantitative in nature but may be qualitative as well. Writing analytics, then, are the metrics that can be calculated from a piece of writing. Simple writing analytics can be collected manually, such as the word count for an essay. Computers and electronic documents create opportunities to collect more and different analytics from writing samples, as well as making certain manual methods much faster. Simple analytics include document word, paragraph, or sentence counts; average words per sentence or paragraph; spell checking. More complex metrics include part-of-speech tagging and semantic role labeling for individual words, grammar checking, and stylistic element checking (Writing-Based Learning Analytics for Education, 2013).

Less common in often-used software products is the use of advanced writing analytics. While Google search makes some use of analytics, much of its algorithm’s computation revolves around ranking pages for suitability to the search (Page, Brin, & Motwani, 1998).

Translators, on the other hand, make much more extensive use of writing analytics, to the point of training their engines with Web documents that include translations, which are themselves ranked (Levy, 2011).

Because WLD and writing difficulties for ADHD focuses on the written composition aspect, ranking and translation of word and sentence are less important of a measure than the cohesiveness of overall writing. However, elements of the ranking can be used to determine the word’s relevance in regard to the written topic (i.e. if the student's writing contains topic flow or cohesion issues; a difficulty that most ADHD students have in the writing, as demonstrated in Table 2 above).

In academia, it is often most convenient to use tools that are either open source or have special permissions to be used for educational and research purposes. Spell checkers and word counters are normally embedded inside other, larger applications such as word processors and web browsers for simple writing analytics. However, there are several stand-alone tools that can be used to build spell-checking functionality into other applications. GNU Aspell is one of the most popular open source libraries for spell checking (Atkinson, 2006). It stores dictionary words in long flat files, and loads them when the library runs, comparing selected words to the dictionary to determine their correctness. Aspell was designed to be able to give suggestions for misspelled words as well.

Beyond simple spelling, there are also tools that attempt to glean more than just correctness and incorrectness. Natural language processing (NLP) packages 'read' text and attempt to computationally break it down into its constituent parts. One of the most famous NLP suites is the Stanford parser, which uses a lexicalized probabilistic context-free grammar (PCFG) for text processing (Klein & Manning, 2003). The result of running the Stanford parser on a text string is a tree-like structure, where the nodes of the tree are phrases and parts of speech labeled with the words written. This tool essentially gives a model of the grammar used, sentence by sentence. While the Stanford NLP suite is useful, it primarily does one thing: part-of-speech tagging. Some NLP suites make many more functions available to developers and users. One example is OpenNLP, an Apache project. OpenNLP is a toolkit for all varieties of language processing. It includes a sentence detector (intelligently finds where a sentence ends), a tokenizer (breaks a sentence into words), a name finder (locates proper nouns and numbers in a sentence), a document categorizer (identifies a document's general subject matter, sorting it into a predefined category), a part-of-speech tagger (much like Stanford NLP), and a chunker (separates a sentence into phrases and word groups without specifying individual parts of speech). OpenNLP is a comprehensive self-contained suite that is ideal for generating a variety of metrics.

Building on the idea of parsing parts-of-speech, there are tools that analyze the parts of speech for scoring the quality of the writing for simple writing analytics, such as spelling and grammar, and more advanced metrics, such as topic flow and cohesive adequacy. Coh-Metrix (Graesser, McNamara, Louwerse, & Cai, 2004) is a web-based information system designed to analyze text and automatically produce measures of written composition for students. Coh-Metrix analyzes texts on over 50 types of cohesion relations and over 200 measures of language, text, and readability. The tool is sensitive to a broad profile of language and cohesion characteristics and has modules that use lexicons, part-of speech categorizers, syntactic parsers, templates, corpora, statistical representations of world knowledge, and other components that are widely used in computational linguistics. Coh-Metrix parses text typed in real-time or pasted in blocks and produces linguistic metrics as output.

Because Coh-Metrix can measure many of the metrics identified when determining writing difficulties in a written composition (such as the ones identified in the "Methods of Measuring Written Difficulties in ADHD Students" section above), the Coh-Metrix tool will likely be used for analyzing student writing data in this research.

When analyzing the writing, many of the studies used correlation analysis as their analysis technique. The study that is being proposed for this research will use correlation analysis as well on a combination of screening tools to diagnose ADHD with WLD. By applying the techniques to a combination of screening tools it is hypothesized that the combination will yield much higher levels of accuracy identifying ADHD with WLD symptoms than what is reported in the literature.

Correlation Analysis Techniques

Correlation is a measure of how strong the relationship is between two variables. Covariance is a measure of how much the two variables change together (Pollard, 1997).

If the greater values of one variable mainly correspond with the greater values of the other variable, and the same holds for the smaller values, i.e., the variables tend to show similar behavior, the covariance is positive. In the opposite case, when the greater values of one variable mainly correspond to the smaller values of the other, i.e., the variables tend to show opposite behavior, the covariance is negative. Covariance indicates a linear relationship between the two variables and the normalized version of the covariance, the correlation coefficient, shows the strength of that linear relationship.

The formula for covariance is as follows:

$$var(X) = \frac{\Sigma x^2}{n} - (\overline{x})^2$$

$$var(Y) = \frac{\Sigma y^2}{n} - (\overline{y})^2$$

$$Cov(X,Y) = \frac{\Sigma(x-\overline{x})(y-\overline{y})}{n}$$

where x is the experimental variable (symptom characteristics), and y is the control variable (classifier characteristics). $\overline{x}$ is defined as the mean of all the x's shown in n

number of tests and $\overline{y}$ is defined as the mean of all the y's shown in the same number of n tests.

and the correlation coefficient is calculated as:

$$r = \frac{Cov(X,Y)}{\sqrt{var(X)}\,\sqrt{var(Y)}}$$

If r is close to 1 then the symptoms are strongly related to the classification terms, if the r is 0 or negative, the symptoms are not related to the classification terms.

Out of the literature, many of the studies used correlation analysis to analyze the metrics they received in order to “learn” the relationship of the input variables to the output variables. Some of the studies used covariance comparison (ANCOVA), cluster analysis and neural networks. These types of concepts are explained below with the method of their technique.

ANCOVA

ANCOVA tests analyze the variance on the experimental and control variables (the variables being the covariates). Using the covariance and correlation calculations mentioned above, the ANCOVA tests can validate (or disprove) the relationships found between the two variables (Pollard, 1997). Casa et. al, used ANCOVA to validate the variance between the ADHD group’s writing and the control group’s writing, using the metrics from the control group as the control variable (Casa, Ferrer, & Fortea, 2011). In a similar fashion, the study for this research can use ANCOVA to validate the variance between ADHD group and control group’s writing as well.

Cluster Analysis

Cluster Analysis separates data input into groups (clusters) based on the similarities the input variables have to each other. The grouping is made from the information in the variables, not by a pre-existing classification (Tan, Steinbach, Karpatne, & Kumar, 2019). The classification (output) is then defined by the groups. Schrank used cluster analysis to define and validate the writing difficulties in the ADHD group's writing samples by breaking the writing data into clusters (spelling, writing fluency, writing content, and editing) and creating the classification of writing difficulties from these groups (Schrank, 2005).

Artificial Neural Networks

Decision tree learning uses decision tree logic (i.e. yes/no factors) as a predictive model (IBM SPSS, 2012). The method maps observations about an item to conclusions about the item's target value. For example, in a diagnosis-by-survey tool, the survey will ask the user a series of questions. Based on the user's answers, the tool will use decision tree logic to predict what the diagnosis will be. As a pattern forms from a series of surveys with similar answer outcomes, the tool will "learn" the decision tree logic and store that pattern as a diagnosis to quickly refer to (i.e. build libraries).

Artificial Neural networks (ANN) combine the decision tree technique (with correlations on the input variables and the output variables (defined classification terms) as its "yes" and "no" factors) with parallel searches on the data. Much like how the human brain accesses different parts of its memory to retrieve information and see correlations between the information for the ending decision, neural networks do the same, using algorithms to make those decisions.

While this technique has not been used for written composition difficulties, it has been used to identify ADHD using EEG tests; with regions of interest (ROIs) that show brain activity being reviewed for the ROI cognitive patterns for ADHD (the brain activity

ROIs being the input variables) (Mohammadi, Khaleghi, Nasrabadi, Rafieivand, & Zarafshan, 2016). ANN has also been used identify children with dyslexia (a learning disorder in which the child has difficulty reading and spelling) using questionnaires that assess the child's reading and spelling ability. The answers of these questionnaires are the input variables for the ANN, with the output (or decision variables) being variables for the dyslexia classification and variables for the non-dyslexia classification (Kohli & Prasad, 2010).

It is the last technique that research uses to create the predictive model for diagnosing ADHD students with WLD. Because ANNs use a Multi-layer perceptron (MLP) architecture, that can run many non-linear functions in parallel (which is explained more in the "Data Analysis" part of the Methodology section) on the input data to predict the outcome, it can learn the diagnostic behavior of diagnosing ADHD with WLD in a student and create a predictive model from it.

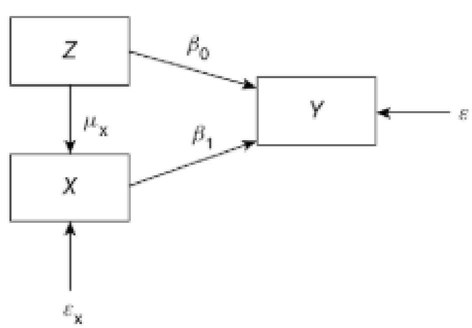
Causal Modeling

While correlation analysis can validate the strength of the input/output variable relationship, it cannot determine if the output variable is a direct effect of the input variable. In order to determine that cause/effect relationship, causal modeling can be used.

Causal models are mathematical models representing causal relationships within an individual system or population. They facilitate inferences about cause-and-effect relationships from statistical data, analyzing if (or how) the input variables (the causes) effect the output variables (the effects), while identifying if there are any other knowledge gaps in the process (Petersen & van der Laan, 2015).

The input and output variables are treated as events, with the effect being measured against the treatment input variables and output variables against the counterfactual input variables and output variables (ex. treatment input being ADHD group variables, counterfactual input being control group variables, and output variables being the DSM output for ADHD and WLD).

These variables can be put into a directed acyclic graph (DAG) as nodes with the correlated probability as an edge, to demonstrate the influence the input variable has on another variable. The nodes indicate if they are direct causes with arrows (edges) and are acyclic (in that a variable does not cause itself). In the case where the variables are continuous (they can take on infinitely many uncountable values), structural equation models (SEMs) can be used to estimate casual relationships in terms of a system of linear equations. There is an equation in a SEM for each variable in the model consisting of the value of its inputs (direct causes) plus some error term (a residual variable produced when the model does not fully represent the actual relationship between independent and dependent variables). An example of this is in the causal structure *X* -> *Y* <- *Z* (that is a model that infers *X* and *Z* are direct causes *Y*). This can be represented by the following structural model in Figure 3:



$$X = \varepsilon_X$$

$$Y = \beta_0 1 + \beta_1 X + \varepsilon$$

Figure 3. Estimating simple regression using SEM.

Where ε_X is the error term of X, Z is a constant (X regressing on Z), and Y is the coefficient of Z (β_0) taking on the value 1 + the coefficient of X (β_1) taking on the value of X (independent variable) + the error term of Y (ε_Y). With Z having a direct effect on Y ($\beta_0 1$) and an indirect effect on Y ($\beta_0 1 + \beta_1 \mu_X$), where μ_X is the mean of X (Blunch, Niels J., 2016).

Of course, putting the equation into a visual model is easier to understand the causal relationship than many equations, which is why tools exists to demonstrate this relationship. One of the tools that can be used is TETRAD V. TETRAD V is an application developed by researchers at Carnegie-Melon University that implements the algorithms developed and explained in Causation, Prediction, and Search (Glymour, Scheines, Sprites, & Ramsey, 2017). These algorithms involve searching for causal interpretations from observed data, and a suite of tools for testing those interpretations. For a given data set, it is possible to derive several different possible causal models by enforcing different assumptions, constraints, and parameters on the data. The parameters are explained more in the “TETRAD V” part of the Methodology section.

Based on lessons learned from this literature review, this thesis will analyze datasets using statistical software and analysis techniques identified above. It will also identify strengths and weaknesses of other screens in relation to the process of diagnosing an ADHD student with WLD. By conducting an observational study on ADHD and typical groups, a data set can be built that encompasses the predictive diagnostic probability of these tools. Further, this dataset can capture every step of the diagnostic process to offer better insights on the analysis and to yield more accurate diagnosis. The raw data will have a correlation analysis run on the symptoms, with the patient data (symptoms from the screening tool) being initially tested against the characteristics of the DSM-V classification for reliability (in regard to the strength of the relationship between the data variables the DSM-V classifier variables). The data will be analyzed to see if the coefficient between the patient data and the classifier is a positive one, the cut off being greater than 0.8 (this number being determined from the first meta-analysis for common screening tools with correlation coefficients closest to the DSM output (Mitchnick, Kumar, Kinshuk, & Fraser, 2016)) to determine the strength of the relationship (or the association). A formalized mathematical model based on the correlated variables can then be created (using IBM SPSS Neural Networks (IBM SPSS, 2012)) to be used in the learning the diagnostic process for ADHD and WLD. A casual model can then be used (using TETRAD V) to view the direct effect relationships between the input and output variable to see what inputs may cause the output to occur. This comprehensive model will provide the basis for predicting the student’s mental health and learning outcomes.

Chapter 3. Methodology

This research addresses the problem of measurement of the relation between ADHD and WLD among adult learners. The previous chapter described the behavioural assessments, the assessments for written expression difficulties, the development and application of analytics (in general and as applied to the ADHD with WLD diagnosis) and the statistical techniques involved in estimating correlation from that data. In this chapter, these concepts are combined into a model that collects the data, analyzing it for quantifiable information, and applying correlation techniques to produce the diagnostic outcomes that will answer the research question.

As part of this research, a software tool named ‘Mental Health Analysis and Diagnostic Service (MHADS)’ has been designed and developed. This software tool works in conjunction with the LAMBDA framework (Boulanger, Seanosky, Pinnell, & Bell, 2019) for storing and processing the data.

MHADS consists of two primary components: a data gathering tool, and a processing tool. The data gathering component has two subcomponents. The first subcomponent collects information on various screens: on a) physical questionnaire, b) behavioural rating scale for ADHD (ASRS), a behavioural rating scale for other mental health disorders (WEISS Record), and c) reaction performance testing (like Conner’s CPT). The second subcomponent collects learner performance data on writing exercises. The second component is developed as a plugin for a writing tool and gathers highly granular information about students’ writing and share it with LAMBDA’s transit database. LAMBDA analyses students’ written content and writing processes to produce various writing related measures. The MHADS processing component then invokes a few algorithms to extract metrics from the physical and behavioural screens, as well as linguistic relationships from students' writing related measures. These relationships are represented in an Artificial Neural Network (ANN) map using IBM SPSS as well as in a casual model with Tetrad V.

This model will provide the basis for predicting the student's mental health and learning outcomes.

Data Collection

Demographics Screen. A demographics screen (Figure 4) collects students' age, gender and any family history of interest to the ADHD diagnosis. The information collected was not mandatory and served to describe the sample groups. While they do not influence the diagnostic outcome at this time of this research, they are of interest for future correlative studies and qualitative analysis as well.

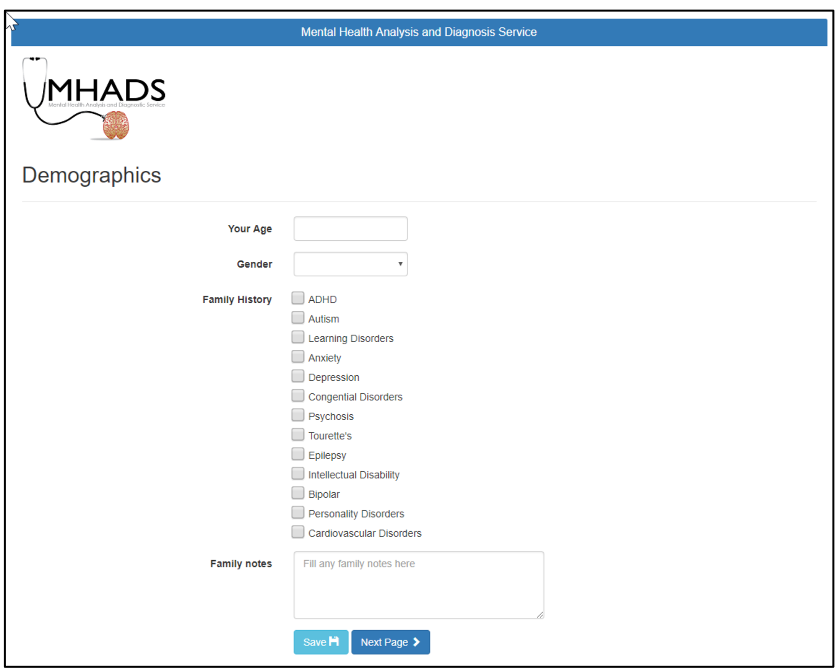


Figure 4. View of demographics questionnaire.

The following four screens (Figures 2, 3, 4 and 5) have been designed based on the outcomes of a meta-analysis (Mitchnick, Kumar, Kinshuk, & Fraser, 2016) on commonly used screening tools for ADHD.

Physical Questionnaire. This questionnaire (Figure 5) collects information about physical health issues that mimic ADHD symptoms (ex. head trauma, hearing/visual problems) (CADDRA, 2014). If the student has any of these issues, they are noted as a comorbidity that could account for the students' ADHD symptoms in the study.

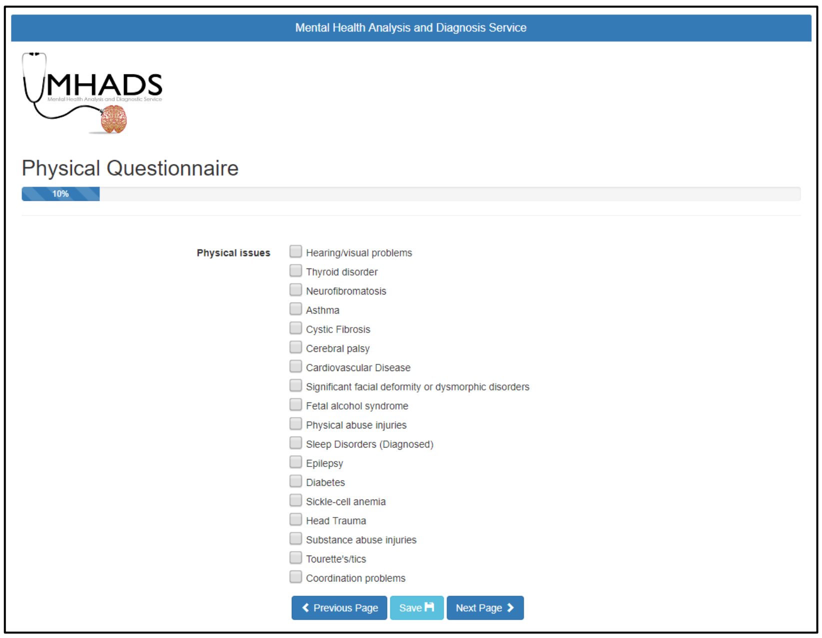
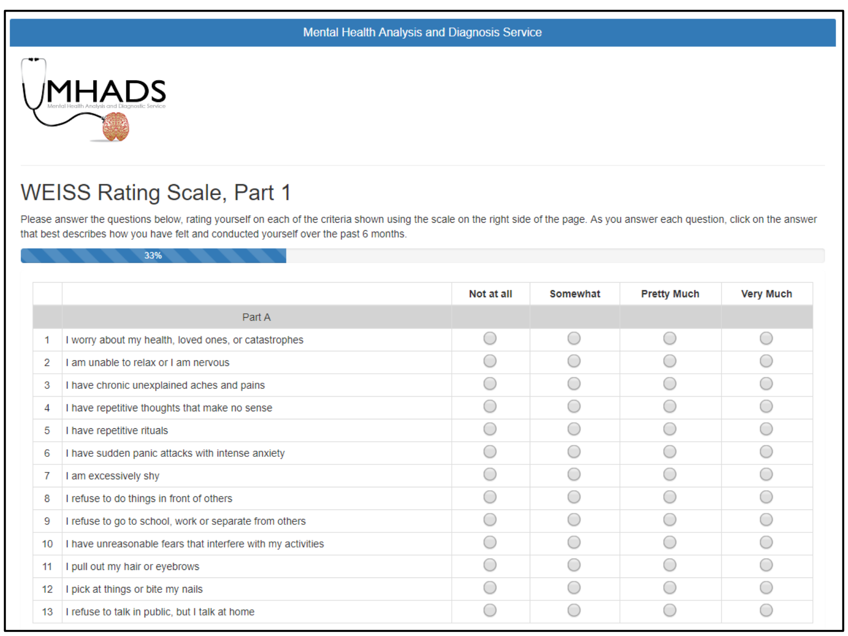


Figure 5. View of screen for physical health issues.

Scores were coded as 0 for any physical issue and 1 for no physical issues; 0 meaning it is difficult to say if the participant fits the criteria for ADHD in this area, since the physical symptom can bias the results and 1 being that the participant has no other physical symptoms. In the previous studies, all ADHD participants sampled did not have any other physical symptoms, so their score was 1. Weighting this score to the

DSM output classifier is shown in the “Data Analysis” part of the “Methodology” section.

WEISS Record Scale. this behavioral self-reporting rating scale collects answers of “Not at all” (coded as 0), “Somewhat” (coded as 1), “Pretty Much” (coded as 2) and “Very Much” (coded as 3) on all behavioral questions (CADDRA, 2014). A modified version of this scale was created to include questions that related to the ADHD classifier symptoms (Figure 6). Answers to the questions in the “Pretty Much” and “Very Much” category filter out other mental health disorders that are similar to ADHD (e.g., anxiety, Tourette’s). Each section is scored by counting a set of questions that are answered with “Pretty Much” or “Very Much” (ex. for questions that revolve around testing for anxiety, answering “Pretty Much” or “Very Much” on “worrying” on “nervousness” indicates that the student is likely not to have ADHD as a predominant disorder, as those traits are not in the ADHD classifier symptoms). A breakdown of the scale’s scoring is found in Appendix B – Scoring Tables (Table B-2).


Mental Health Analysis and Diagnosis Service

MHADS

WEISS Rating Scale, Part 1

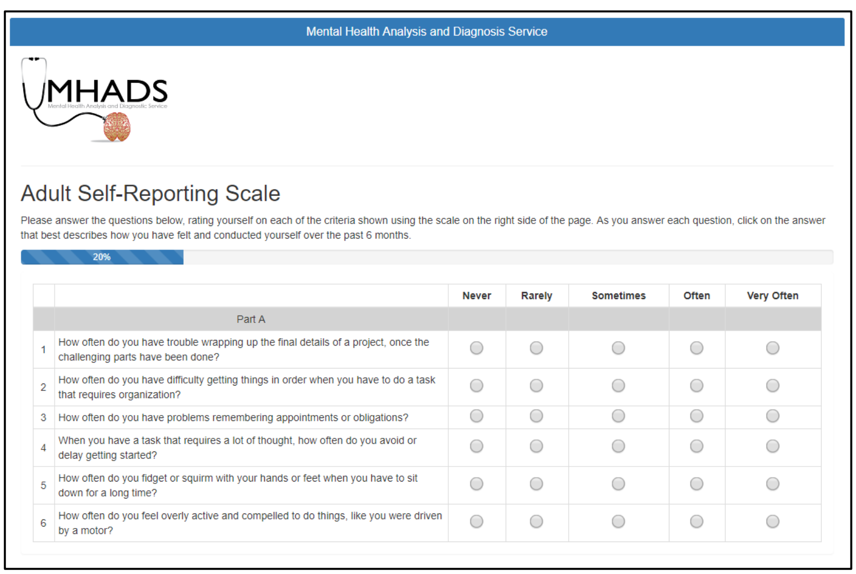
Please answer the questions below, rating yourself on each of the criteria shown using the scale on the right side of the page. As you answer each question, click on the answer that best describes how you have felt and conducted yourself over the past 6 months.

33%

		Not at all	Somewhat	Pretty Much	Very Much
	Part A				
1	I worry about my health, loved ones, or catastrophes				
2	I am unable to relax or I am nervous				
3	I have chronic unexplained aches and pains				
4	I have repetitive thoughts that make no sense				
5	I have repetitive rituals				
6	I have sudden panic attacks with intense anxiety				
7	I am excessively shy				
8	I refuse to do things in front of others				
9	I refuse to go to school, work or separate from others				
10	I have unreasonable fears that interfere with my activities				
11	I pull out my hair or eyebrows				
12	I pick at things or bite my nails				
13	I refuse to talk in public, but I talk at home				

Figure 6. View of screen for mental health issues.

Adult Self-Reporting Scale (ASRS). this behavioural self-reporting rating scale (Figure 7) collects answers of "Never" to "Very Often" on the questions (questions 1-6 in Part A) (CADDRA, 2014). The number of questions that answered "Often" and/or "Very Often" are counted towards the total number for that attribute group, with "Often" and "Very Often" being scored as 1 count. From the count, the model looks for how many identifiers matched the classifier (in the classifier for adult ADHD, a count of 4 "Attention" deficiency identifiers needed to consider the student having an attention-deficit) (World Health Organization, 2015). For example, if a person entered "Often" on "How often do you have trouble wrapping up the final details of a project, once the challenging parts have been done?", that would count as 1 point towards the ADHD score, as the question relates to the inattentiveness factor of the classifier. Answering 4 or more out of 6 in part A, indicates the person has a greater propensity to ADHD. Additional questions are asked for Part B, but they are optional and purely for probing purposes (additional information or cues that the student may have of ADHD), but does not measure/count towards the diagnostic classification of ADHD)


Mental Health Analysis and Diagnosis Service

MHADS
Mental Health Analysis and Diagnostic Service

Adult Self-Reporting Scale

Please answer the questions below, rating yourself on each of the criteria shown using the scale on the right side of the page. As you answer each question, click on the answer that best describes how you have felt and conducted yourself over the past 6 months.

20%

		Never	Rarely	Sometimes	Often	Very Often
	Part A					
1	How often do you have trouble wrapping up the final details of a project, once the challenging parts have been done?					
2	How often do you have difficulty getting things in order when you have to do a task that requires organization?					
3	How often do you have problems remembering appointments or obligations?					
4	When you have a task that requires a lot of thought, how often do you avoid or delay getting started?					
5	How often do you fidget or squirm with your hands or feet when you have to sit down for a long time?					
6	How often do you feel overly active and compelled to do things, like you were driven by a motor?					

Figure 7. View of screen for ASRS.

Response-Time Based Continuous Performance Test (CPT). Based off the Conners CPT3 test for ADHD, this test tracks response-times via keyboard inputs from the student. The response times are tallied as scores that fit within the dimensions of the ADHD classifier (Conners, 2013). For example, scores on commissions' reaction times (number of times the user pressed the spacebar when not seeing an object "X" on the screen (Figure 8)) are scored in the "Inattentiveness" category, with a score higher than 75% being classified towards the "Attention" deficiency part of the DSM Classifier. The score can also be scored in the "Impulsivity" category, which can also be classified towards the "Attention" deficiency, since impulsivity is a symptom in the DSM-V ADHD classifier.

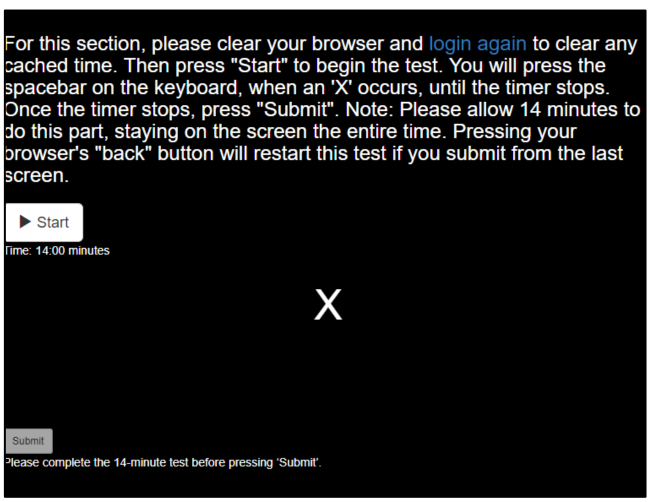


Figure 8. View of screen for Response-Time Based CPT.

The test uses 23 foils (or non-targeted letters: A, B, C, D, E, F, G, H, I, J, K, L, M, O, P, Q, R, S, U) and 200 targets (targeted letter: X) presented in intervals of 1, 2 or 4 seconds. With the scoring (Conner CPT 3 Progress Sample Report, 2018) checking for:

- number of correct trials (i.e. hits on "X") - less than 70% indicating inattentiveness and impulsivity
- number of missed targets, i.e. Not hitting the "X" (omission errors) - more than 70% of the time indicating inattentiveness
- number of missed targets, i.e. Hitting the wrong letter (commission errors) - more than 70% of the time indicating hyperactivity and impulsiveness
- correct reaction time - speed less than 100 ms indicates hyperactivity and inattentiveness - optional measure, not very conducive to study

Other optional measures are:

- correct reaction time SD
- time for completion

The optional measures are recorded for statistical purposes (Conner CPT 3 Progress Sample Report, 2018).

Writing Expression Performance Testing. As noted in the "Methods for Measuring Writing Difficulties in ADHD Students" part of the "Background" section, since there is no standard screen for WLD, a second meta-analysis was completed on the studies of ADHD students with written language and written expression difficulties. The outcomes of the meta-analysis yielded the following metrics to measure WLD in ADHD students:

Errors:

- Spelling errors (norm = 25 words in 500 words)
- Grammatical errors (norm = 25 errors in 500 words)

- Morphosyntactic Errors (norm = correct use of he/she 70% or more in 20 sentences--match sentence tense ("he" in previous sentence, against "he" in next sentence))
- Morphosyntactic Errors (norm = correct use of past/present/future tense 70% or more in 20 sentences--use Stanford NLP for ontology lemmas ("was" in first sentence, against "liked" in sentence)
- Time sequence errors (look for if "third" comes before "second", capitalization in the first word, ending punctuation in the last word, adverb after verb, etc.: norm = 44 in 500 words, scoring as per the Wechsler Individual Achievement Test (WIAT) (Breaux & Frey, 2017)

Values higher than the respective norms, except for morphosyntactic and time sequence errors, indicates inattentiveness and written composition impairment. For example, if the spelling and/or grammatical errors in a 500 word essay has a count of 30, then this score goes towards the “inattentive” category of the ADHD classification (since the student “fails to give close attention to details or makes careless mistakes in work or other activities”) and the “spelling accuracy” (deficiency) category of the WLD classification since the student shows “impairment in spelling accuracy”.

Numbers:

- Number of Sentences = 40 sentences is norm in 500 words
- Number of words = 500 is norm

Values lower than the respective norms indicate inattentiveness. For example, if a student writes 30 sentences and 300 words, the score goes towards the “inattentive” category of the ADHD classification, since the student may not be breaking the sentence up appropriately (ex. run-on or incomplete sentences) or not explaining the concept in more detail (i.e. more words). Therefore, they “often [have] difficulty organizing tasks and activities”. The student may also have “grammar and punctuation accuracy” and “clarity or organization of written expression” impairments associated with the WLD classification, based on this score.

Pairing

- Connective Cohesion (number of sentences paired together based on relationship) – Checks synonyms and connectors for connectivity
- Cohesive Adequacy (number of incomplete sentences) - Check for punctuation mark at the end of a sentence. Checks for verb ending a sentence (ex. "The boy was."). Checks for other for incomplete ties.

Prevalence of inattentiveness is inferred if more than 5 concepts are missed or found to be unrelated out of a total of 10 concepts. For instance, with connective cohesion, if the adjacent sentence for a written topic does not have a synonym or connector that is similar to the previous sentence, then it is an unrelated to the topic (ex. I like ice cream. It’s hot outside). A related topic would be “I like ice cream. The ice cream tastes good on a hot day.” For cohesive adequacy, an example would be “I like.” or “I like ice cream the ice cream tastes good”. These incidences of incomplete ties and connectivity would have a score that would go towards the “inattentive” category of the ADHD classification, since the student would again demonstrate they “often [have] difficulty organizing tasks and activities”. The student may also have “grammar and punctuation accuracy” and “clarity or organization of written expression” impairments associated with the WLD classification, based on this score.

If the score for any of these error metrics is higher than the norm, except for morphosyntactic and time sequence errors, it is an indication of spelling deficiencies (phonological, orthographic, and morphological aspects of regularly and irregularly spelled words), written language composition deficiencies at a sentence level (judgment in grammar and inflectional morphology) and deficiencies at a written convention level (punctuation and paragraph formation).

For morphosyntactic and time sequence errors, if the error metrics are lower than the respective norms, then it is indication of deficiencies at the written convention level (again, punctuation and paragraph formation). Spelling and grammar correction were not tracked within the tool as students needed the ability to compose their thoughts and then paste it in the tool. However, future improvements on the tool could capture this information if the student was to write within the tool itself.

From these scores, a Writing Analytics CPT screen (Figure 9a) like the writing analytics tool, MI-Writer (Clemens C. , 2014), can tracking real-time counts for simple writing analytics (such as the number of spelling and grammar errors), with a writing analysis tool like Coh-Metrix (Figure 9b) can track static text count for advanced writing analytics (such as morphosyntactic errors, connective cohesion, and cohesive adequacy). These counts would measure WLD in an ADHD student (more detail in the "Coh-Metrix" section on how the metrics would be gleaned). With the Writing Analytics CPT screen, the student could either type in their written composition or paste it from a word processing program. The same could be done for the Coh-Metrix tool. The counts could then be analyzed for the ADHD Student writing profile (which was mentioned in the

"Methods for Measuring Difficulties in ADHD Students" part of the "Review of the Literature" section).

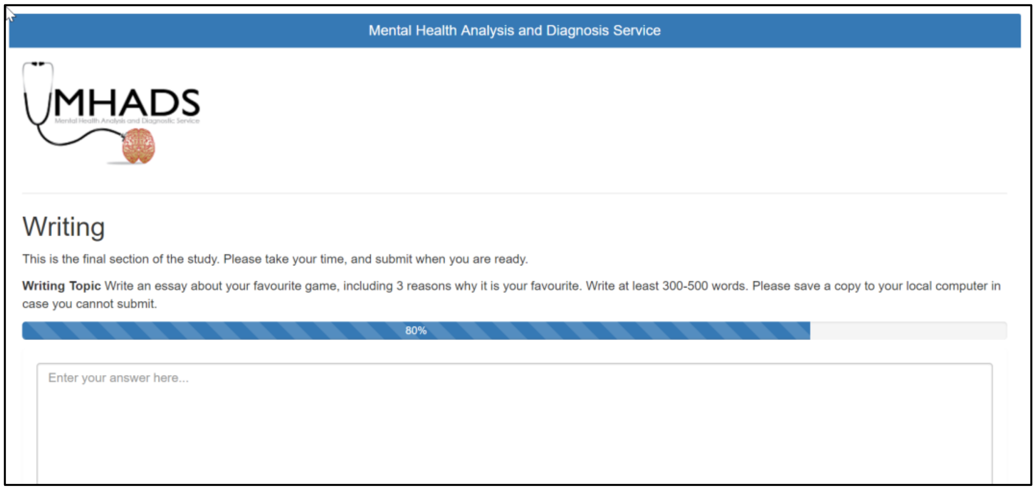
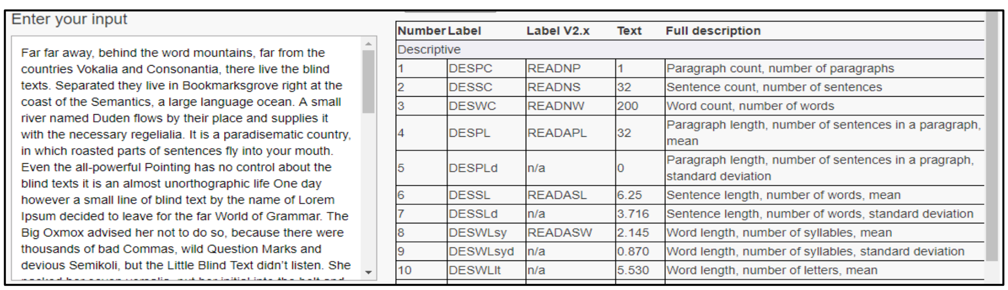


Figure 9a. View of screen for Writing Analytics CPT in MHADS.



Number	Label	Label V2.x	Text	Full description
Descriptive				
1	DESPC	READNP	1	Paragraph count, number of paragraphs
2	DESSC	READNS	32	Sentence count, number of sentences
3	DESWC	READNW	200	Word count, number of words
4	DESPL	READAPL	32	Paragraph length, number of sentences in a paragraph, mean
5	DESPLd	n/a	0	Paragraph length, number of sentences in a pragraph, standard deviation
6	DESSL	READASL	6.25	Sentence length, number of words, mean
7	DESSLd	n/a	3.716	Sentence length, number of words, standard deviation
8	DESWLsy	READASW	2.145	Word length, number of syllables, mean
9	DESWLsyd	n/a	0.870	Word length, number of syllables, standard deviation
10	DESWLlt	n/a	5.530	Word length, number of letters, mean

Figure 9b. View of screen for Writing Analysis (Coh-Metrix) tool.

Coh-Metrix

As mentioned in the "Writing Analytics" part of the Background session in Chapter 2, Coh-Metrix (Graesser, McNamara, Louwerse, & Cai, 2004) is a web-based information system designed to analyze text and automatically produce measures of written composition for students. Coh-Metrix analyzes texts on over 50 types of cohesion relations and over 200 measures of language, text, and readability.

Coh-Metrix parses text typed in real-time or pasted in blocks and produces linguistic metrics as output. The base of the scores is set at 1000 words. Coh-Metrix metrics that are of relevance to the measuring of WLD in ADHD students (specifically the ADHD student writing profile noted in the "Methods for Measuring Difficulties in ADHD Students" part of the "Background" section) are listed in Table 3 below.

Table 3

Coh-Metrix Writing Metrics Relevant to the "WLD in ADHD Student" Profile

Metric	Description	Relevancy to Profile
DESWC	Counts of the number of words	Number of words
DESSC	Counts of the number of words sentences.	Number of Sentences
WRDPRP3s	The incidence score of pronouns, third person, single form (he, she, etc.) per sentence. Looks for new instances and matched against wording in the sentence ("he" matching with "his", "she" matching with "hers"). If fewer instances, the correct pronoun is being used in the sentence.	Morphosyntactic Errors (inconsistent use of pronouns like he/she in sentences)
SYNTEMP	The repetition score for tense and aspect in the joining sentences. The repetition score for tense is averaged with the repetition score for aspect (i.e. "was" being matched against past tense of the action. For example: "He was elated. All his classmates liked him." The higher the repetition score the more the correct tense is being used.	Morphosyntactic Errors (inconsistent use of past/present/future tense)

CNCTemp	The incidence score of temporal connectives to indicate order (when, then, next) in the paragraph. Comparing sentences, if a new instance of the connective is indicated, then the sentence is evaluated for topic flow (ex. “He went to the store then he went to his car.”). Again, if less new instances, then correct order is being used.	Time sequence errors (look for if "third" comes before "second", capitalization in the first word, ending punctuation in the last word, adverb after verb, etc.)
CNCTempx	The incidence score of extended temporal connectives to indicate order (first, second, third) in the paragraph. Comparing sentences, if a new instance of the connective is indicated, then the sentence is evaluated for topic flow (ex. “First he went to the store, second he went to his car.”). This score indicates the presence of connectives; but then is manually evaluated. Again, the lower the score, the more the correct order is being used.	Time sequence errors (look for if "third" comes before "second", capitalization in the first word, ending punctuation in the last word, adverb after verb, etc.)
LSASS1	The mean Latent Semantic Analysis (LSA) cosines for adjacent, sentence-to-sentence units. This score measures how conceptually similar each sentence is to the next sentence. This more similar the sentences are the higher the score.	Connective Cohesion (number of sentences paired together based on relationship) - synonyms and connectors for connectivity

SYNLE	The mean number of words before the main verb of the main clause in sentences. This is a good index of working memory load.	Cohesive Adequacy (number of incomplete sentences) - Check for verb ending a sentence ("was."). Check for incomplete ties.
PCREFz	A text with high referential cohesion contains words and ideas that overlap across sentences and the entire text, forming explicit threads that connect the text for the reader. Low cohesion text is typically more difficult to process because there are fewer connections that tie the ideas together for the reader.	Cohesive Adequacy (number of incomplete sentences) - Check for incomplete ties.

These metrics, plus the spelling and grammar error counts collected through the MHADS tool, are put into a spreadsheet (Figure 10), which can be fed into IBM SPSS to create an Artificial Neural Network model (which is explained in the “Data Analysis” section).

Physical Sample Data																			Total for not having ADHD		Correlatio	Weight in Study	Scale
PH1	PH2	PH3	PH4	PH5	PH6	PH7	PH8	PH9	PH10	PH11	PH12	PH13	PH14	PH15	PH16	PH17	PH18						
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0		100%	20%	1
WEISS Sample Data																			Total for having ADHD				
OQ1	OQ2	OQ3	OQ4	OQ5	OQ6	OQ7	OQ8												Total for ODD	Must have			
0	0	2	3	1	2	3	1												4	at least 4	12.50%	3%	1
AQ1	AQ2	AQ3	AQ4	AQ5	AQ6	AQ7	AQ8	AQ9	AQ10	AQ11	AQ12	AQ13							Total for Anxiety				
2	2	2	2	1	1	3	1	0	0	2	0	3							4	4	12.50%	3%	1
D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13							Total for Depression				
0	1	2	3	3	2	3	3	1	0	0	0	0							7	at least 5	12.50%	3%	1
MQ1	MQ2	MQ3	MQ4	MQ5	MQ6	MQ7													Total for Mania				
0	1	2	3	3	1	2													4	at least 3	12.50%	3%	1
SQ1	SQ2	SQ3	SQ4	SQ5	SQ6	SQ7	SQ8	SQ9	SQ10	SQ11	SQ12								Total for Social Skills				
0	1	2	3	3	3	2	3	2	1	1	1								7	at least 5	12.50%	3%	1
PQ1	PQ2	PQ3	PQ4	PQ5	PQ6	PQ7													Total for Psychosis				
0	1	2	3	3	2	2													5	at least 5	12.50%	3%	1
LQ1	LQ2	LQ3	LQ4	LQ5	LQ6	LQ7	LQ8												Total for Learning Disorder				
0	1	2	3	2	0	1	3												4	4	12.50%	3%	1
PDQ1	PDQ2	PDQ3	PDQ4	PDQ5	PDQ6	PDQ7	PDQ8	PDQ9	PDQ10	PDQ11									Total for Personality Disorder				
0	2	3	3	1	2	2	3	3	0	0									7	at least 5	12.50%	3%	1
ASRS																			Total for having ADHD				
Q1	Q2	Q3	Q4	Q5	Q6														Total for ADHD				
2	3	3	1	2	2														4	at least 5	100%	20%	1
CPT																							
NumCorr																			Total for ADHD				
14																			4	out of 20	30%	6.00%	1
OmErr																							
15																				out of 20	30%	6.00%	1
ComErr																							
15																				out of 20	30%	6.00%	1
CorrRT																							
50																				at least 1(	10%	2.00%	1
Writing Sample																							
DESWC	300																		Total for ADHD		9%	2.00%	1
DESSC	11																				9%	2.00%	1
SE	30																				9%	2.00%	1
GE	45																				9%	2.00%	1
WRDPRP3s	0.45																				9%	0.50%	1
WRDPRP3p	0.5																				9%	0.50%	1
SMTEMP	0.5																				9%	2.00%	1
CNCTemp	55																				9%	2.00%	1
LSASS1	6																				9%	0.50%	1
SYNLE	6																				9%	0.50%	1
PCREFz	6																				10%	2.00%	1

Figure 10. Values from sample data and their weight in the study. Highlighted fields being the fields that are counted.

Data Analysis

To analyze the data collected, the correlation and causal modeling techniques mentioned in the "Background" section were applied to the data. To create the correlation model (Artificial Neural Network) and causal model, the statistical software IBM SPSS and Tetrad V were used. This is explained more in the following sections.

Using an Artificial Neural Network (ANN)

Recall how Artificial Neural networks (ANN) takes many input variables to predict the outcome of the output variable. Much like how the human brain accesses different parts of its memory to retrieve information and see correlations between the information for the predicting the outcome, neural networks do the same, using algorithms to make that prediction. However, instead of drawing from memory, it is fed input data as a starting point. The input values are represented by nodes in the input layer, algorithms on those nodes are represented by a hidden layer to do the calculation (i.e. weight nodes used to calculate the algorithms), and the outcome values are represented by nodes in the output layer. In these layers, “multilayer perceptron” uses a “nonlinear activation function” (correlation functions) on the nodes (except the input nodes) to define the output of that node. That output changes the weights of the hidden layer and the nonlinear activation function is run again by the inputs to define an output closer to the actual output node. Although the algorithms flow in one direction initially, the network of layers is not completely a feedforward node (neural) network. Since they have to go back to get an output closer to the actual output node, the it is instead is a neural network that uses “backpropagation”.

As an example, suppose the ADHD DSM classifier was made up of 5 inattentive attributes and 5 hyperactive attributes that had to be present in order to meet the ADHD definition. Figure 11 illustrates how the neural network would work in the context of this example, and the rules that would have to happen to contribute to the confirmation of the diagnosis. The red data inputs would each have the black metrics (scales) in a hidden layer, with weights attached to them in relation to the output (the classifier). The weights are random at first. While the input metrics themselves could not change, the weight they are given (above the blue weight indicators below) would change. In this case, in a linear activation, the WEISS input (0, 0) is not an indicator for ADHD, because of its low weight to the classifier (output through a path is 0 H, 0 I). But, because there is a nonlinear activation on the WEISS point scale, other inputs of a higher weight (ASRS or CPT) are revealed as indicators (have a path output that is close the 5 H, 5 I), and are then used toward the overall score for the DSM classifier (5 H, 5 I). The path output of those ASRS or CPT inputs are then the new weights and are fed back in the model to see if they can get even closer to the output attributes (5 H, 5 I). This is called “retraining”. Once it is as close to the output as possible, that is the new training model for future inputs. It is this “retraining” cycle in the different layers (input, hidden and output) that defines the model as a “multilayer perceptron” one. If it was not part of cycle (i.e. the output values were not fed back into the weights for retraining), it would be a seen as a single-layer perceptron only in a feed-forward network. Because it’s is going back to adjust the weights and then retrain the model, it is seen as “backpropagation”.

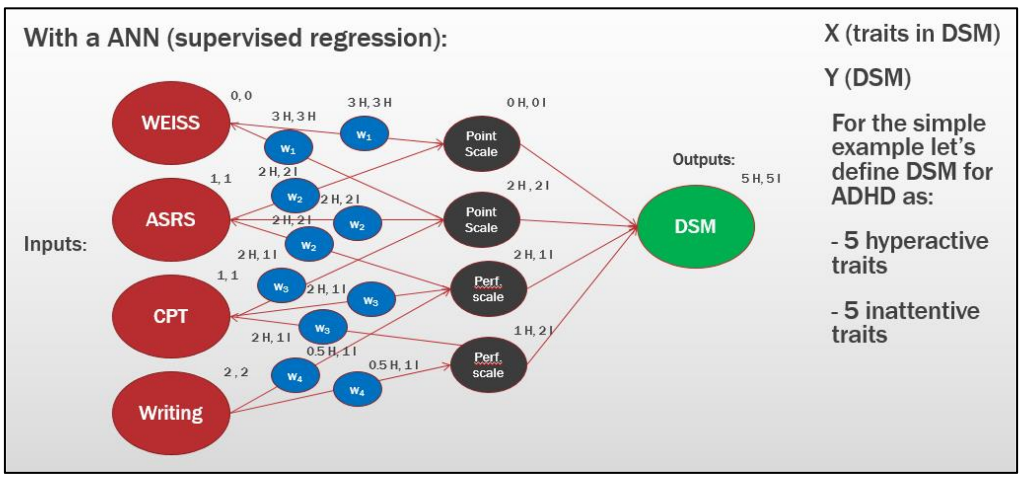


Figure 11. Example of using screening method inputs, with hidden layer metrics (scales0 to get the desired output (DSM classifier).

How it is determined if an input’s weight is “close” to the output, is if its path (or algorithm) has a strong “synaptic weight”. The formula to calculate the synaptic weight strength is shown in Figure 12, where y_j is the estimated output node, w is the weight of the input node, and x is the input node. Taking the above example, say we want to calculate the synaptic weight strength for the ASRS point scale path. The estimated output node would be the WEISS input path to the point scale, plus the ASRS input to the point scale, plus the CPT input to the ASRS point scale. So $w_1x_1 + w_2x_2 + w_3x_3$, which is (3,3)*(0,0) + (2,2)*(1,1) + (2,1)*(1,1) = (4 H , 2 H). This is the estimated value for the inputs to the hidden layer (point scale for ASRS), which we'll call y_1 (Mazur, 2015).

$$y_j = \sum_i w_{ij} x_i \ \text{ or } \ \mathbf{y} = w\mathbf{x}.$$

Figure 12. Calculation for synaptic weight (w) with initial input node (x) to determine the estimated output node (y).

Now we need to estimate the output from the hidden layer node (ASRS point scale) to the output node (DSM). But what tells the model to activate the calculation function so that we have an output applied from hidden layer in the calculation when estimating the output of the hidden node to the output node? In other words, what tells the above calculation to fire? That would be activation function, which is shown in Figure 13.

$$\sigma(z) \equiv \frac{1}{1+e^{-z}}.$$

Figure 13. Sigmoid function as the activation function for hidden layer node (z).

Where (z) is the estimated value of the input to that hidden layer (or y_1 from Figure 12). In this example, the calculation for the activation function would be 1/1 + e log -(4,2). Which would be 1/(1.02, 1.14) = (0.98, 0.88). This is now the value of hidden layer (which, for this example can be called h_1).

Multiplying the hidden layer value (h_1) to the weight of the ASRS point scale (2 H, 2 I), we get (0.98, 0.88)*(2,2) = (1.96, 1.76), which is the new estimated value of the hidden layer to the output node, which, for this example can be called y_2.

Needing to activate (y_2) now, since that calculation won't activate on its own, we apply the activation function again. This time it would be 1/1 + e log -(1.96, 1.76). Which would be 1/(1.14, 1.17) = (0.88 H, 0.85 H). This is the estimate output now for the DSM output node, which is we'll call y_3. This is nowhere near the actual output that is required for the DSM classifier (5 H, 5 H); but the difference can be found and applied to the new weight to get a weighted model that is closer to the DSM output.

To find the difference in the actual output to the estimated output, another formula (loss function) can be used to calculate the error value (Figure 14).

$$E_T\left(w\right) = \sum_{m=1}^{M} E_m(w)$$

where

$$E_m\left(w\right) = \frac{1}{2}\sum_{r=1}^{R} \left(y_r^{(m)} - a_{I:r}^{m}\right)^2$$

Figure 14. Error value on the actual output (y) minus the estimated output (a).

In this example, y_3 is now a, and the actual output is y. That means that error value would be ½ ((5,5) – (0.88,0.85))^2. This is a sum of error calculation, meaning if there were more possible outputs from the ASRS point scale to the DSM output, their output would be added to other estimates. Calculating this out, the error value would be: ½ (4.12, 4.15)^2 or (8.49, 8.61). Which is considerably large (we want to get to an error value of (0,0) if we can). This error can be denoted as the error value E.

Now that the error value is determined, the weights should be adjusted to reflect this. Starting with the last weight that the model got output from, which would be the weight for the hidden layer or (2, 2), backpropagation occurs. The model calculates (using the formula in Figure 15) the partial derivative of the error value (gradient value) to this weight, working backwards until it has touched on all weights in the network (or non-linear paths), by subtracting the gradient value from the weight value.

$$\begin{aligned}\frac{\partial E}{\partial w_{ij}} &= \frac{1}{2}\sum_{k\in K}(a_k - t_k)^2 \\ &= \sum_{k\in K}(a_k - t_k)\frac{\partial}{\partial w_{ij}}a_k\end{aligned}$$

Figure 15. Gradient value formula to adjust the weights in backpropagation.

In this example, the gradient value on the hidden layer is the derivative (∂)E/∂ of the hidden layer node (2,2). Since the derivative of the hidden layer node is unknown, it needs to be split out to ($\partial E/\partial y_3$)*($\partial y_3/\partial y_2$)*($\partial y_2/\partial(2,2)$. Doing so, the values for $\partial E/\partial y_3$ are 2*1/2((5,5)-(0.88, 0.85)$^{2-1}$*-1+0 = (4.12, 4.15); the values for $\partial y_3/\partial y_2$ are (0.88, 0.85)-(1-((0.88, 0.85)) = (0.76, 0.7); the values for $\partial y_2/\partial(2,2)$ are 1*(0.98, 0.88)*(2,2)$^{(1-1)}$+0+0 =(0.98, 0.88). So, the (∂)E/∂(2,2) would be (4.12, 4.15)* (0.76, 0.7)* (0.98, 0.88) = (3.07, 2.56). This is what the model needs to change the hidden layer node weight (2,2) by.

So now that the model knows what it needs to change in the weight by to get a more accurate output, a learning rate can be attached to it, so the model can learn this change for the other weights at an appropriate speed. If the learning rate is too fast (i.e. is a much larger number than proportionate to gradient value), the gradient descent can inadvertently increase rather than decrease the training error. If the learning rate is too slow (i.e. is a much smaller number than proportionate to gradient value), the training rate is not only slower, but may become permanently stuck with a high training error. To measure the learning rate, we use our final function in Figure 16.

$$\theta \leftarrow \theta - \eta \frac{\partial E}{\partial \theta}$$

Figure 16. Calculating the rate at which the model learns.

In this example, to update the hidden layer node with this learning rate, the hidden layer node weight (2,2) is subtracted from the learning rate (η)*the gradient value on the hidden layer (3.07, 2.56). The model starts with a learning rate of 0.5 as a default. Then the calculation would be: (2,2) – (0.5)*(3.07, 2.56) = (0.46, 0.72), which is now the new weight for the hidden layer node.

The same is done for the other weights (w_1 and w_2), and then forward fed again starting at function 1 with the new weights to see if the model can get an error value that is minimal and an output closer the DSM (5,5). This goes on and on (going back and forth) for many loops until we achieve that goal. However, doing those calculations would be time-consuming and prone to error if done by hand (Kumar, 2018). Instead using a tool like IBM SPSS to do these calculations help with not only calculating but visualizing the model.

An example that was used as a theoretical model for the process was done in a previous study (Mitchnick, et al., 2017), with input from the results of the set of studies from the literature review. Table 4 produces data that is used to train the neural network model.

Table 4

Demographics and correlation values matched against the DSM classifier

Study	Demographics			Input Screens Weighted					Total
	Mean Age	Gender	Family History	Physical	WEISS	ASRS	CPT	Written CPT	DSM Output for WLD and ADHD
Casa, Ferrer, & Fortea (2011)	12	M	Dyslexia	1	0.3	0.9	0.6	0.85	0.8
Capodieci, Esposito, Mirandola, & Re (2014)	10	M	Depression	1	0.2	0.8	0.75	0.75	0.7
Lienemann & Reid (2006)	9	M	Bipolar	1	0.2	0.75	0.8	0.8	0.8
Schrank (2005)	14	F	None	1	0.1	0.85	0.6	0.62	0.65
McQuade (2010)	9	M	Depression	1	0	0.85	0.6	0.78	0.75

Rodríguez, Grünke, González-Castro (2015)	13	M	Tourette's	1	0.1	0.85	0.6	0.8	0.8
Miranda, Baixauli, Colomer (2013)	21	M	ODD, Anxiety	1	0.2	0.8	0.8	0.75	0.75
Molitor, Langberg, Evans	12	F	ODD	1	0.4	0.8	0.8	0.72	0.8

For training the model to evaluate the ADHD student data's association to WLD, the student data (input) is run through a multilayer perceptron for learning the algorithm that would yield the strongest connection from the student data nodes (input nodes from the covariates: average WEISS, ASRS, CPT and Written CPT correlation values, excluding Physical, since it is a factor of 0/1, but not a scaled measure (increasing value)) to the outcome node (output node for the ADHD with WLD classifier). As "backpropagation" occurs, the amount of error can be calculated based on the strength of the connection between an input data node and the output classifier node. The amount of error gives an indication of how close the input node's relationship is to the output node. This error is considered in the weight of the values in the hidden layer (synaptic or connection weights), which determines if the values reflect the same amount of error in the connection weights of other student data. If they do not, the input is excluded as it does not follow the general pattern of the other input for the desired outcome. Changes to the weights can influence the updates on the model, but it requires quite a few interactions (using the method mentioned above) and studying of the error to get to a significant level of changes to the weights.

To obtain the association for ADHD classification with WLD and to validate it, the data in Table 4 was run in a multilayer perceptron neural network through IBM's SPSS Statistics 24. The average correlated input values of the studies in Table 4 were inputted as nodes into the network model, and the correlated output of the ADHD and WLD classifier were added as the output node. Running the software's multilayer perceptron algorithm on the input nodes (a correlated weight entered as a weight node for the hidden layer), the following model diagram was created (see Figure 18). Studies were considered valid with respect to the training model if the amount of error in the connection weights of the study data were in relation to the other studies' data (not outside the linear relationship of the input node to the output node); this technique evidenced for error amounts in the previous literature for ANNs (Mohammadi, Khaleghi, Nasrabadi, Rafieivand, & Zarafshan, 2016). All eight studies were considered valid (see Figure 17).

Case Processing Summary

		N	Percent
Sample	Training	6	75.0%
	Testing	2	25.0%
Valid		8	100.0%
Excluded		0	
Total		8	

Network Information

Input Layer	Covariates	1	WEISS
		2	ASRS
		3	CPT
		4	WritingCPT
	Number of Units[a]		4
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	DSMOutput
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Figure 17. Statistics for training and testing in IBM SPSS.

The perceptron also produces a network diagram (see Figure 18) from the studies inputs and weights. The dark blue lines are synaptic (or connection) weights; meaning they indicate a strong connection between the input data node and the output classifier node.

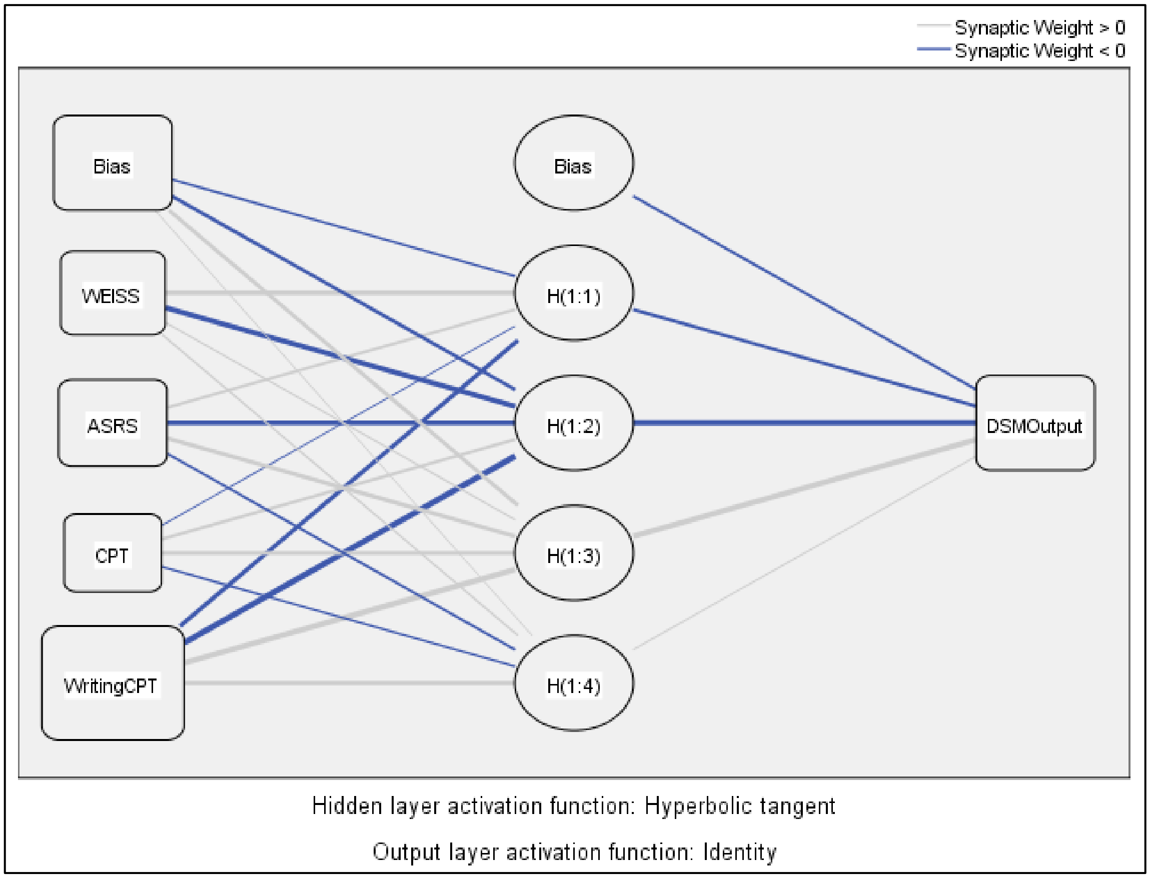


Figure 18. First pass of correlation data for training in SPSS for ADHD with WLD.

As shown above, there are many paths from the input node to the DSM Output, that have a strong synaptic weight. However, we don't know if this is it; as in, if this model displays the strongest weight/node relationship or if we can get a stronger one? To find out, the model must be run again to see if it displays the same relationship, a stronger relationship or a weaker one. However, the strong blue line in Figure 18 already shows that there is a link of ADHD to WLD (Writing Performance in the WritingCPT). This is reinforced in a previous study where the WEISS Record and the WritingCPT are also prevalent in measures for WLD and had a similar connection for ADHD students (Mitchnick, et al., 2017).

Model Summary

Training	Sum of Squares Error	.217
	Relative Error	.087
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	1.011
	Relative Error	.[b]

Dependent Variable: DSMOutput

Figure 19. Sum of Squares Error on the first pass.

Running the second pass, the network diagram looks like this:

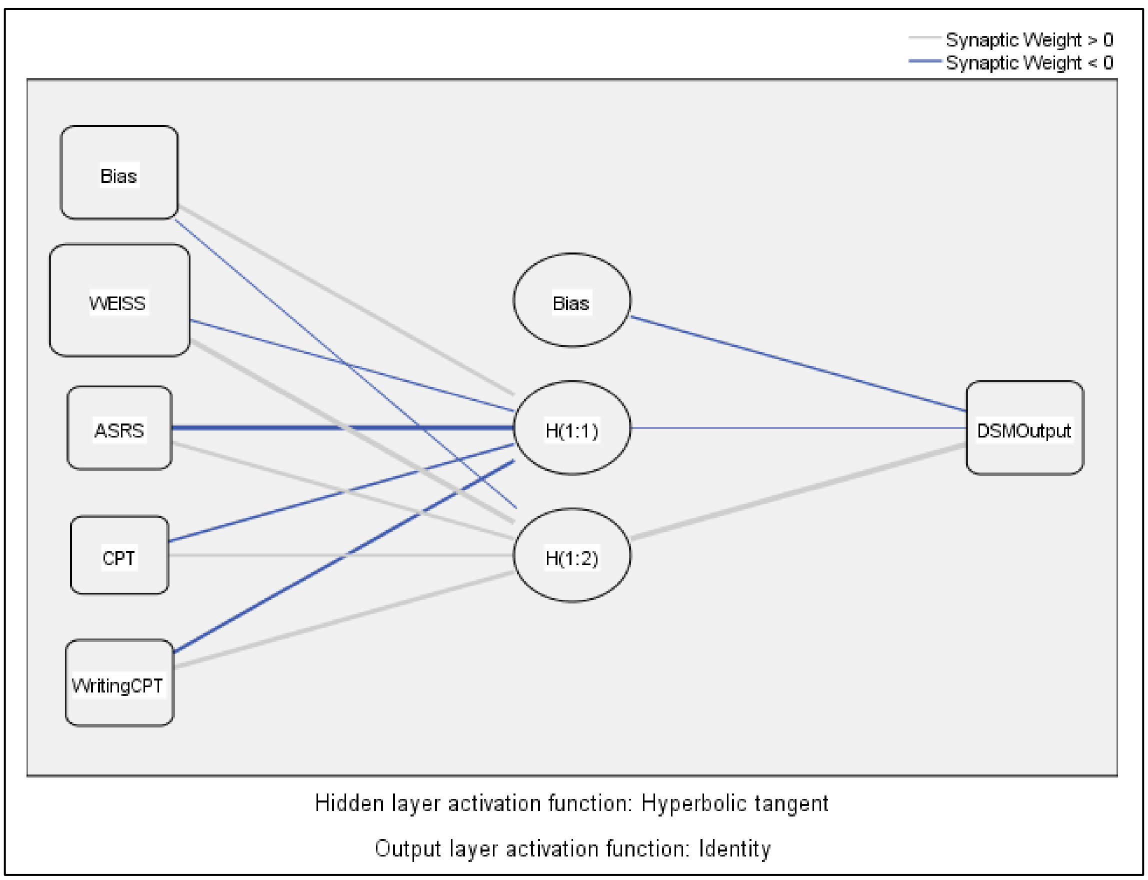


Figure 20. Second pass of correlation data for training in SPSS for ADHD with WLD.

And the sum of squares error looks like this:

Model Summary

Training	Sum of Squares Error	.119
	Relative Error	.080
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	9.176
	Relative Error	.906

Dependent Variable: DSMOutput

a. Error computations are based on the testing sample.

Figure 21. Sum of Squares Error on the second pass.

Demonstrating that the few more iterations may have a model that is closer to the desired output.

Now that we have demonstrated the strength of the relationship between the input and output variables, we must see if the relationship is a causal one. Using a causal modeling software like Tetrad V will show us that relationship.

TETRAD V

TETRAD V is an application developed by researchers at Carnegie-Melon University that implements the algorithms developed and explained in Causation, Prediction, and Search (Glymour, Scheines, Sprites, & Ramsey, 2017). These algorithms involve searching for causal interpretations from observed data, and a suite of tools for testing those interpretations. For a given data set, it is possible to derive several different possible causal models by enforcing different assumptions, constraints, and parameters on the data.

As an example, the following model was created in Tetrad V for writing metrics on typical students. The model is a structural equation model (SEM) and uses Fast Greedy Equivalence Search (FGS) over writing competencies to find causal connections (this is done through a covariance matrix between the metrics) (Clemens, Kumar, Boulanger, Seanosky, & Kinshuk).

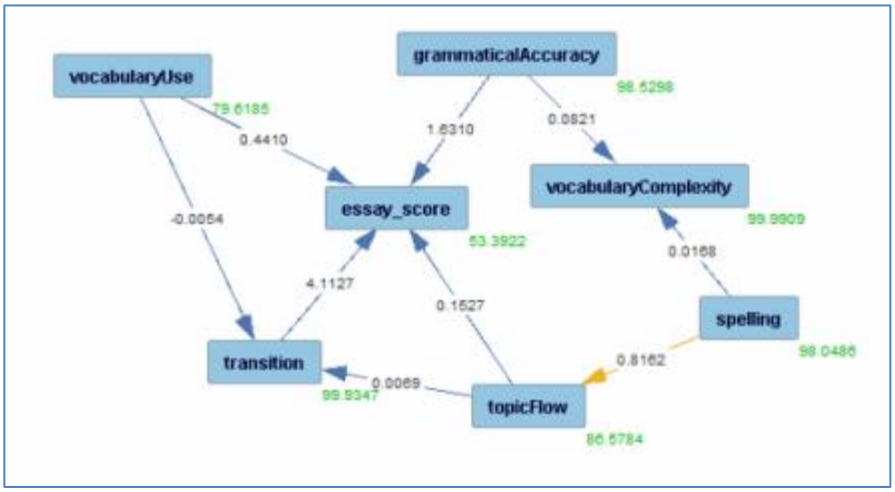


Figure 22. SEM from FGS Search over Competences. Final Essays illustrates observed metrics (blue boxes) that can be used for casual modeling (Clemens, Kumar, Boulanger, Seanosky, & Kinshuk). The correlations between the metrics (numbers in black) to the final essay score are indicated in the diagram. The mean for the metric is indicated in green.

The blue lines are direct paths to the next factor, and the yellow lines are indirect paths. For instance, in the above diagram, spelling has a direct effect on vocabularyComplexity. However, it has an indirect effect on topic flow. Therefore, the correlation from spelling to the essay score is low, indicating that other factors have more of an influence on essay_score than spelling.

The data used for this diagram was normalized student data. However, the same method could be applied to ADHD students' writing competencies to create a covariance matrix for WLD. The metrics that can be used to see if this model fits are:

Spelling

Spelling is a potential cause in the system of variables with competences and final writing data. An undirected edge between spelling and topic flow that indicates the causal direction is uncertain in typical student writing data. Spelling also influences vocabulary complexity. Adding a full event data set (that is, adding a data set that is made up of tracking events as a student types) can put spelling into topic flow as a cause. Further, it can reverse the causal direction of the spelling-vocabulary complexity edge, which indicates some uncertainty in this direction. Spelling can also become a cause of transition in full event data. Another undirected edge can be added between grammatical accuracy and spelling because of this cause. The FGS searches over the data and can indicate where there are latent common causes between all the adjacencies that connect into the spelling competence.

Topic Flow

In the competence variable set over final writing data, it is possible that the topic flow variable may be exogenous. There is an undirected edge in the underlying pattern between topic flow and spelling from the typical student writing data. Otherwise, topic flow influences both transition and essay score. The relation between topic flow and essay score remains consistent in typical student writing data. However, topic flow becomes an effect of spelling, vocabulary use (with a negative coefficient) and transition. The FGS can search these variable sets to indicate any latent common causes between all these relationships.

Grammatical Accuracy

Grammatical accuracy is exogenous in the simplest case, affecting only essay score and vocabulary complexity. With full event data over the competences, the edge between grammatical accuracy and vocabulary complexity can be undirected. Grammatical accuracy becomes a cause of vocabulary use, transition, and possibly spelling (via another undirected edge). The FGS algorithm can make an interesting switch of the causal direction between grammatical accuracy and transition, which would cause all the other variables adjacent to grammatical accuracy to have latent common causes because of this switch.

Other metrics could be used for the casual model as well. These three metrics (Clemens, Kumar, Boulanger, Seanosky, & Kinshuk)just illustrate what can be done with the model that is already created for typical student writing data. The metrics used for the experimental study will show the causality between the metrics in the “Causal Model of WLD” part of the “Results” section.

Chapter 4. Results

To answer if there is a computational model that can identify and integrate measurable factors that contribute to ADHD and WLD diagnosis to produce a more accurate diagnostic outcome, an experimental study was conducted.

The experimental study (see Appendix C – Figure 30 for study approval and Figure 31 and 32 for study information and registration and consent form) was conducted at Athabasca University between April to June 2018 to compare the results of the theoretical model in the "Data Analysis" section of the Methodology against real-student data. The study was blinded. That is, a third party collected responses from students and communicated with students who consented to participate. The third party also removed any personally identifiable information from the data before passing it to the researcher.

The data was obtained from two groups: an ADHD group (n=45), and a control group (n=65). To recruit students for the ADHD group, the researcher approached the Department of "Access to Students with Disabilities" (ASD) at Athabasca University. ASD personnel then sent a message to students who had been formally diagnosed with ADHD (i.e. diagnosed by a medical professional) to take part in the study. Students who had no association with the ASD were then recruited for the control group. The control group received their invitation to participate a full month after the message was sent to the ADHD group of students. This gap in messages was required to prevent members of the two groups from communicating with each other, thus avoiding a bias in the sample. Further, the wording of the messages was changed in the registration and the study's data collection screens (as indicated in the Methodology above) so that there would not be an internal bias on student performance.

Of the 77 students that registered for the ADHD group, 54 started the study, with 45 completing the study, and of the 103 students registered for the control group, 81 started the study, with 65 completing the study. While participants were encouraged to complete the study in a month, a strict timeline was not set. This allowed the researcher to measure any time difference in completing the study between the two groups.

37% of the ADHD group finished within the recommended timeframe of one month while 63% took 2 or more months to complete. On the other hand, 100% of the control group completed the study within the recommended timeframe of one month.

The study was designed to take about 3 hours for a typical student to complete the study from start to finish. Since it would be difficult to sustain attention for that long, sessions were saved so that participants could interleave their interactions with the study material. As a result, the researcher was able to track when the student dropped off from the study. The results are summarized below in Table 5:

Table 5

Drop off Point for Students who Did Not Complete the Study

	ADHD Group (n=9)	Control (n=16) and (n adjusted for ADHD group size)
Completion to ASRS	1	1 (.7)
Completion to Questionnaire (WEISS Part A)	1	0 (0)
Completion to Reaction-Based CPT	3	7 (4.6)

Completion to Written CPT	4	8 (5.3)

It was surprising to see that more control participants had dropped off from completing the two CPT tasks than ADHD participants. This anomaly requires more studies to determine if this was a one-off case or a repeatable pattern. The two CPT tasks did require sustained attention from the participants. However, it was not surprising that more control students completed the study overall. Similar study completion rates were observed from previous studies where there were higher completion rates of control participants than ADHD participants.

Demographics

The results for the demographics in Table 6 was different than the literature review indicated, with more females taking part in each group. The average age was 33 for the ADHD group and 35 for the control, making the average age higher than previous studies ages, which mainly fell between 18-24 for university students.

Table 6

Demographics for Students Participating in the Study

	ADHD Group (n=45)	Control Group (n=65)	Total*
Males	15	11	26
Age 20-29	6	4	10
Age 30-39	6	3	9
Age 40-49	2	2	4
Age 50-59	1	2	3
Females	30	53	83

Age 20-29	12	15	27
Age 30-39	12	25	37
Age 40-49	5	7	12
Age 50-59	1	6	7
Family History			
No Family History**	4	26	30
ADHD	25	5	30
Autism	0	3	3
Learning Disorders	12	2	14
Anxiety	30	24	54
Depression	26	30	56
Congenital Disorders	3	1	4
Psychosis	3	1	4
Tourette's	1	1	2
Epilepsy	3	2	5
Intellectual Disability	4	0	4
Bipolar	10	8	18
Personality Disorders	5	6	11
Cardiovascular Disorders	9	16	25

*1 control participant in the 20-29 age bracket did not identify as male or female

**3 participants did not know their family history as they were adopted

While most of the ADHD group had a history of ADHD in their family, both groups had almost as much of anxiety and depression in their family. Those who answered that they had did not have any family history of mental health or learning disorders came primarily from the control group (n=26) instead of the ADHD group (n=4), inferring the hypothesis that family history in these areas (particularly with ADHD) may play a part in the student having WLD and/or ADHD. Although this is inferred in the literature review as well, more research would need to be done in this area to confirm this hypothesis.

Physical Comorbidities

The results for the Physical Comorbidities were surprising. It was predicted in the previous studies from the literature review that more than half of students in the ADHD group would have no physical comorbidities (that is, their score would be 1). However, less than half of the students in the ADHD group had no physical comorbidities in this study. The results are indicated in Table 7 below:

Table 7

Student Counts for Physical Comorbidities

	ADHD Group (n=45)	Control (n=65) and (n adjusted for ADHD group size)
No Physical Comorbidities	17	30 (20.8)
Hearing/Visual Problems	15	17 (11.8)
Thyroid Disorder	9	6 (4.2)
Neurofibromatosis	0	0 (0)

Asthma	9	10 (6.9)
Cystic Fibrosis	0	0 (0)
Cerebral Palsy	3	4 (2.8)
Cardiovascular Disease	0	0 (0)
Significant facial deformity or dysmorphic disorders	0	0 (0)
Fetal alcohol syndrome	0	0 (0)
Physical abuse injuries	6	1 (0.7)
Sleep Disorders	8	3 (2.1)
Epilepsy	2	1 (0.7)
Diabetes	4	9 (6.2)
Sickle-cell anemia	1	0 (0)
Head Trauma	7	3 (2.1)
Substance abuse injuries	5	0 (0)
Tourette's/tics	1	0 (0)
Coordination problems	3	2 (1.4)
More than 1 Comorbidity		
2 Comorbidities	8	9 (6.2)
3 Comorbidities	3	3 (2.1)
4 Comorbidities	3	2 (1.4)
6 Comorbidities	2	0 (0)
7 Comorbidities	2	0 (0)

These results indicate that ADHD is usually accompanied by a physical disorder as well. While most participants had hearing/visual problems, indications were lacking about the use of aids to address these disorders (such as the hearing aids or glasses). It was assumed based on previous studies that sleep disorders and head trauma would be the next set of physical disorders that accompany ADHD; however, most participants reported thyroid disorder and asthma for this study. It would be worth exploring connection between these dominant disorders and ADHD in another set of studies. Since these physical disorders do not influence the presence of writing difficulties, the numbers were not counted towards the measuring for WLD.

However, to look at the probability of the presence of a physical disorder having an effect on ADHD, a correlation was done on overall ADHD criteria (DSM Output in Appendix A – Table 1) in comparison to the physical weighted score (Physical Weighted in Appendix A – Table 1). This shows the relationship of the physical disorder to the ADHD classifier in Table 8.

Table 8

Correlation of Physical Disorders in Relation to ADHD Classifier

	Mean	SD	Correlation (r)	p-value (p < 0.05)	Confidence Level (95% CI)
ADHD Group (45)	0.20	+-0.26	0.67	< .00001	[0.124, 0.276]
Control Group (65)	0.24	+-0.27	0.82	< .00001	[0.174, 0.306]

For both groups (ADHD and control), the relationship to the ADHD classifier is strong, meaning that the test has strong enough relationship to detect the symptoms that are not indicative of ADHD (i.e. other physical disorders), though still not indicative of determining ADHD alone. Calculating the p-value, we get an insignificant p-value for both groups (Stangroom, Pearson Correlation Coefficient Calculator, 2019). Since both groups have a p-value less than 0.05, the hypothesis that both values are significantly different is rejected and that the physical disorder is dependent on the ADHD classifier.

Because it is a nominal scale though (0 for having a physical symptom mimicking ADHD vs 1 for having no symptoms that mimic ADHD), the results of this test might count as a bias in the ANN model because the results are subjective. This is demonstrated in the Table 9, which shows the Chi-Square Independence Test (Stangroom, Chi-Square Calculator, 2019), to see if the difference between the participant groups is by chance, or if the physical test is really an indicator of symptoms that are not indicative to ADHD.

Table 9

Contingency Table for association with ADHD and Control Groups on Physical Disorders

	No physical disorders	Physical Disorders	Total
ADHD Group (45)	17	28	45
Control Group (65)	30	35	65
Totals	47	63	110
Chi-Square			0.762
p-value			0.383

Since the p-value is greater than 0.05, it is not significant, meaning the difference between the groups is by chance and are not likely to do with the ADHD classification.

Behavioural Comorbidities that Correlate with ADHD (WEISS Record)

The results in Table 10 for the WEISS record were mixed. A significant number of participating students in the ADHD group reported depression issues that correlated to ADHD. As the WEISS Record tests for attention only issues and hyperactivity issues (not the combined type of ADHD), questions asking about inattentiveness only or hyperactivity only were part of the record. Not surprisingly, a considerable number of participants in the ADHD reported having attention only issues and hyperactivity only issues. Interestingly enough, the participants of the ADHD group or control group did not report learning disorders issues.

Table 10

Student Counts for Behavioural Comorbidities that Could be Counted towards the Prevalence of ADHD

	ADHD Group (n=45)	Control (n=65) and (n adjusted for ADHD group size)
No Behavioural Comorbidities at all	5	25 (17.3)
Behavioural Issues that exist but do not Count towards ADHD	4	6 (4.1)
Anxiety	1	1 (0.7)
Depression	19	12 (8.3)
Mania	8	1 (0.7)
Social Skills	4	1 (0.7)

Psychosis	0	0 (0)
Learning Disorders	0	0 (0)
Personality Disorder	2	1 (0.7)
Attention Issues	18	3 (2.1)
Hyperactivity Issues	14	3 (2.1)
Opposition Defiance Disorder	6	3 (2.1)

To test for the significance of the behavioural disorder scale (Table 11) in relation to the ADHD classifier, we do the same calculation we did for the physical disorder:

Table 11

Correlation of Behavioural Disorders in Relation to ADHD Classifier

	Mean	SD	Correlation (r)	p-value (p < 0.05)	Confidence Level (95% CI)
ADHD Group (45)	0.09	+-0.10	0.03	0.841	[0.0608, 0.119]
Control Group (65)	0.03	+-0.06	0.35	0.004	[0.0154, 0.0446]

Again, for both groups (ADHD and control), the relationship to the ADHD classifier is weak, meaning there is not a strong enough relationship for the behavioural test alone to detect the presence of ADHD (which stands to reason, since it is primarily used to identify other disorders than ADHD). Calculating the p-value, we get an insignificant p-value for ADHD ($p > 0.05$), but not for the control group ($p < 0.05$), meaning the behavioural disorders are not significant (or dependent on the ADHD classifier) for the ADHD group. While it has low significance for this group, it will likely be counted in the ANN model, since there are elements of the scoring that are related to ADHD and WLD—just not enough to be a test of its own.

Since this is an ordinal scale though (that is, it has a Likert-type scale that scores 0-3 instead of 0 or 1), a Mann-Whitney U test (Stangroom, Mann-Whitney U Test Calculator, 2019) can be run on the ADHD group values and the subset of the Control group values (that is, 45 participants of that group) to see if these groups are independent of each other. If they are, then the assumption is that the chances of having behavioural disorders differ between ADHD participants and control participants. Doing this calculation, our z-score is 3.357 (which is a normalized value for our sample size), and our p-value is .00078 which is less than 0.05. This p value means that the score is significant and the chances of having behavioural disorders differ between the ADHD participants and control participants.

Adult Self-Reporting Scale for ADHD

The results in Table 12 for the Adult Self-Reporting Scale were surprising as well. Though these tests were subject to student bias as the student was self-reporting, previous studies in the literature review (Simon, Czobor, Bálint, Mészáros, & Bitter, 2009) predicted that the ADHD group would have more than half of students answering "Often" or "Very Often" for the first 6 ADHD questions (as they were indicative of ADHD), instead of less than half as observed in this study. The results are indicated below:

Table 12

Student Counts for the Adult ADHD Self-Reporting Scale

	ADHD Group (n=45)	Control (n=65) and (n adjusted for ADHD group size)
Answering More than 4 “Often” or “Very Often” for the first 6 ADHD questions	22	4 (2.8)
Answering 3 or less of the “Often” or “Very Often” for the first 6 ADHD questions	23	61 (42.2)
Answering 6-12 “Often” or “Very Often” for the last 12 ADHD probing questions*	27	9 (6.2)
Answering 0-5 “Often” or “Very Often” for the last 12 ADHD probing questions*	18	56 (38.8)

*while alluding to the prevalence of ADHD, not used in the actual rating

More than 20 control students did not answer “Often” or “Very Often” for the first 6 ADHD questions, and more than 10 control students did not answer “Often” or

"Very Often" for the next 12 probing questions. These numbers align well with numbers from the previous studies from the literature review in that a significant number of control group participants would not have indicated "Often" or "Very Often" for any of the ADHD questions.

To test the significance of the ASRS scale (Table 13) in relation to the ADHD classifier, we do the same calculation we did for the behavioural disorder:

Table 13

Correlation of ASRS Scoring in Relation to ADHD Classifier

	Mean	SD	Correlation (r)	p-value ($p < 0.05$)	Confidence Level (95% CI)
ADHD Group (45)	0.11	+-0.08	0.312	0.037	[0.0866, 0.133]
Control Group (65)	0.03	+-0.05	-0.004	0.981	[0.0178, 0.0422]

Again, for both groups (ADHD and control), the relationship to the ADHD classifier is weak, meaning there is not a strong enough relationship for the ASRS test alone to detect the presence of ADHD, though the ADHD group shows a stronger correlation than the control group. Calculating the p-value, we get an significant p-value for the ADHD group as well, and an insignificant p-value for the control group, meaning the test falls in line with being are significant (or dependent on the ADHD classifier) for the ADHD group, while the test falls in line with the control group in the results not being dependent on the ADHD classifier.

Since this is an ordinal scale as well, a Mann-Whitney U test (Stangroom, Mann-Whitney U Test Calculator, 2019) can be run on the ADHD group values and the subset of the Control group values (that is, 45 participants of that group) to see if these groups are independent of each other. If they are, then the assumption is that there is a chance of having different ASRS scores between the ADHD participants and control participants. Doing this calculation, our z-score is 4.88217 (which is a normalized value for our sample size), and our p-value is $< .00001$ which is less than 0.05. This p value means that the score is significant and the chances of having ASRS scores differ between the ADHD participants and control participants.

Response-Based Continuous Performance Testing (CPT) for ADHD

The results in Table 14 were surprising for this test. Contrary to previous studies, the ADHD group were more accurate than the control group in clicking on the target, indicating that they had more attentiveness to the task. However, the control group was quicker at clicking (responding). There were more incorrect responses for the ADHD group though, which were in line with the response-based CPTs from the previous studies; this score indicated that sustained attention was an issue for the ADHD group.

Table 14

Average Response Times and Hits for Each Group

	ADHD Group (n=45)	Control (n=65) and (n adjusted for ADHD group size)
Number of times target was hit correctly	158.8	156.8 (108.6)

Time between responses (seconds)	1.0	0.9 (0.6)
Number of times target was not hit (or incorrect target was hit)	11.5	7.7 (5.3)
Correct reaction time consistency (seconds)	0.4	0.5 (0.3)

As the number of times the “X” was hit was more than 140 out of the 200, both groups on average did not show inattentiveness or impulsivity; though there were 5 ADHD participants who had less than 75% of correct trials, and 6 control participants who had less than 75% correct trials. And while on average, the number of missed targets (not hitting the “X”) was not more than 75% (indicating inattentiveness), 7 ADHD participants did have more than 75% of missed targets and 8 control participants had more than 70% of missed targets, demonstrating this test is not conducive on its own for determining ADHD in participants. The fragility of this test is also indicated by the optional measure of the correct reaction time being observed in less than half the ADHD and the control participants. That is, 20 ADHD and 16 control participants were above the 100 ms (Conner CPT 3 Progress Sample Report, 2018) for the correct response reaction time. Were the study a more a little more conducive, more control participants would have been above the 100 ms in their reaction time to the correct response, since a reaction time of less than 100 ms is indicative of inattentiveness in the participant based on the measures from the Data Collection part of the "Methodology" section.

To measure the significance of the CPT score (Table 15) in relation to the ADHD classifier, we do the same calculation we did for the ASRS disorder:

Table 15

Correlation of Reaction-Based CPT Scoring in Relation to ADHD Classifier

	Mean	SD	Correlation (r)	p-value (p < 0.05)	Confidence Level (95% CI)
ADHD Group (45)	0.082	+-0.007	0.034	0.826	[0.078, 0.082]
Control Group (65)	0.080	+-0.006	-0.101	0.423	[0.0785, 0.0815]

Again, for both groups (ADHD and control), the relationship to the ADHD classifier is weak, meaning there is not a strong enough relationship for the CPT test alone to detect the presence of ADHD, though the ADHD group shows a stronger correlation than the control group. Calculating the p-value, we get an insignificant p-value for the both groups, meaning the test is not significant (or dependent on the ADHD classifier) for the either group. Still, it will be counted as in the ANN as there are elements that do correlate to the ADHD classifier in the previous research.

Since this is an interval scale, another correlation test can be run on the ADHD group values and the subset of the Control group values (that is, 45 participants of that group) to see if these groups are independent of each other. If they are, then the hypothesis is that there is a chance of having different CPT scores between the ADHD participants and control participants. Table 16 shows how strong that assumption is.

Table 16

Correlation of Reaction-Based CPT Scoring between the ADHD and Control Group

	Mean	SD	Correlation (r)	p-value (p < 0.05)	Confidence Level (95% CI)
ADHD and Control Group	0.082	+-0.007	0.128	0.406	[0.078, 0.082]

Doing this calculation, the correlation is weak, indicating that the scores do not share a relationship, and even though they differ from each other, it is not in a significant way according to the p-value. Since the p-value is greater than 0.05, the it is likely that the values are different by chance and not due to being related.

Writing Continuous Performance Testing (CPT)

The results were interesting for both groups. The norm was low for word count and sentence count (Mitchnick, et al., 2017). While the test asked for at least 300-500 words written, both groups averaged at over 300 words and over 18 sentences in their written performance task. This indicates that both groups would have written about 25-30 sentences for a 500-word task, placing them at a higher level of writing level (Average: Grade 9) than the previous studies’ indication of 40 sentences per 500-words (Average: Grade 4.5) task. The results of the written performance tests are shown below in Table 17.

Table 17

Average Scores for Written Performance Metrics

	ADHD Group (n=45)	Control (n=65) and (n adjusted for ADHD group size)
Average Number of Words	367.5	390.5 (270.3)
Average Number of Sentences	18.04	19.4 (13.5)
Number of Students with Sentence Count to be considered for Normal Score	15	31 (21.5)
Number of Spelling Errors	0.4	0.5 (0.3)
Number of Grammatical Errors	2.2	1.8 (1.2)
Morphosyntactic Incidence (he/she consistency – WRDPRP3s)	2.4	3.5 (2.4)
Morphosyntactic Repetition (tense check - SYNTEMP)	0.9	0.8 (0.6)
Time Sequence Incidence - when, then, next (CNCTemp)	20.1	19.9 (13.8)
Time Sequence Incidence (first, second, third CNCTempX)	14.4	15.1 (10.5)
Connective Cohesion - consistency of sentence pairing (LSASS1)	0.2	0.2 (0.1)
Connective Cohesion - mean of words before main verb of a main clause (SYNLE)	4.0	4.2 (2.9)
Reference Cohesion - words and ideas that overlap across sentence to connect text (PCREFz)	0.9	0.6 (0.4)

Both groups were well within the norm (≥15) for spelling and grammar errors in the number of words, so there was no marked difference to indicate inattentiveness there. Nor was there a difference in the morphosyntactic errors (correct use of pronouns and tense 63% of the time or more in 18 sentences (Mitchnick, et al., 2017)); though on average, the ADHD group used the correct tense for sentences more frequently than the control. Both groups were well within the norm (≥26.4 (Breaux & Frey, 2017)) for time sequence errors, though on average, the control group had less errors than the ADHD group.

Both groups on average were in the norm for connective cohesion and cohesive adequacy (Mitchnick, et al., 2017); meaning on average, each group had less than 5 missed concepts out of the 10 described in the topic. However, 18 control participants showed a prevalence of inattentiveness with more than 5 missed concepts, and 7 ADHD participants showed a prevalence of inattentiveness with more than 5 missed concepts.

- Spelling errors (norm = 25 words in 500 words)
- Grammatical errors (norm = 25 errors in 500 words)
- Morphosyntactic Errors (norm = correct use of he/she 70% or more in 20 sentences--match sentence tense ("he" in previous sentence, against "he" in next sentence))
- Morphosyntactic Errors (norm = correct use of past/present/future tense 70% or more in 20 sentences--use Stanford NLP for ontology lemmas ("was" in first sentence, against "liked" in sentence)
- Time sequence errors (look for if "third" comes before "second", capitalization in the first word, ending punctuation in the last word,

adverb after verb, etc.: norm = 44 in 500 words, scoring as per the Wechsler Individual Achievement Test (WIAT) (Breaux & Frey, 2017)

Values higher than the respective norms, except for morphosyntactic and time sequence errors, indicates inattentiveness and written composition impairment. For example, if the spelling and/or grammatical errors in a 500 word essay has a count of 30, then this score goes towards the "inattentive" category of the ADHD classification (since the student "fails to give close attention to details or makes careless mistakes in work or other activities") and the "spelling accuracy" (deficiency) category of the WLD classification since the student shows "impairment in spelling accuracy".

Numbers:

- Number of Sentences = 40 sentences is norm in 500 words
- Number of words = 500 is norm

Values lower than the respective norms indicate inattentiveness. For example, if a student writes 30 sentences and 300 words, the score goes towards the "inattentive" category of the ADHD classification, since the student may not be breaking the sentence up appropriately (ex. run-on or incomplete sentences) or not explaining the concept in more detail (i.e. more words). Therefore, they "often [have] difficulty organizing tasks and activities". The student may also have "grammar and punctuation accuracy" and "clarity or organization of written expression" impairments associated with the WLD classification, based on this score.

Pairing

- Connective Cohesion (number of sentences paired together based on relationship) – Checks synonyms and connectors for connectivity

- Cohesive Adequacy (number of incomplete sentences) - Check for punctuation mark at the end of a sentence. Checks for verb ending a sentence (ex. "The boy was."). Checks for other for incomplete ties.

Prevalence of inattentiveness is inferred if more than 5 concepts are missed or found to be unrelated out of a total of 10 concepts. For instance, with connective cohesion, if the adjacent sentence for a written topic does not have a synonym or connector that is similar to the previous sentence, then it is an unrelated to the topic (ex. I like ice cream. It’s hot outside). A related topic would be “I like ice cream. The ice cream tastes good on a hot day.” For cohesive adequacy, an example would be “I like.” or “I like ice cream the ice cream tastes good”. These incidences of incomplete ties and connectivity would have a score that would go towards the “inattentive” category of the ADHD classification, since the student would again demonstrate they “often [have] difficulty organizing tasks and activities”. The student may also have “grammar and punctuation accuracy” and “clarity or organization of written expression” impairments associated with the WLD classification, based on this score.

To test the significance of the Written CPT score (Table 18) in relation to the ADHD classifier, we do the same calculation we did for the CPT disorder:

Table 18

Correlation of Reaction-Based CPT Scoring in Relation to ADHD Classifier

	Mean	SD	Correlation (r)	p-value (p < 0.05)	Confidence Level (95% CI)
ADHD Group (45)	0.559	+-0.194	0.526	0.0002	[0.502, 0.616]

Control Group (65)	0.547	+-0.172	0.549	< .00001	[0.505, 0.589]

For both groups (ADHD and control), the correlation coefficient is over 0.50, meaning there is a relationship but not enough to detect the presence of ADHD with the Written CPT alone (a correlation that could possibly make that claim would have to have a coefficient < 0.80 (Mitchnick, Kumar, Kinshuk, & Fraser, 2016)). Calculating the p-value, showed a significant p-value for the both groups, meaning the test is dependent on the ADHD classifier for both groups. Interestingly, the control group has a slightly higher correlation and significance.

Since this is an interval scale, another correlation test can be run on the ADHD group values and the subset of the Control group values (that is, 45 participants of that group) to see if these groups are independent of each other. If they are, then the hypothesis is that there is a chance of having Written CPT scores between the ADHD participants and control participants that relate to each other. Table 19 shows how strong that assumption is.

Table 19

Correlation of Written CPT Scoring between the ADHD and Control Group

	Mean	SD	Correlation (r)	p-value (p < 0.05)	Confidence Level (95% CI)
ADHD and Control Group	0.559	+-0.194	0.0533	.728041	[0.502, 0.616]

Doing this calculation, the correlation is weak (≥0.50), indicating that the scores do not share a relationship, and even though they differ from each other, it is not in a significant way according to the p-value. Since the p-value is greater than 0.05, it is possible that the values are different by chance and not due to being related.

Despite this very similar scoring in the CPTs, it will be interesting to input these numbers into the ANN, to see what the overall relationship is.

Actual Model Using ANN

To assess the overall performance of each participant, a compilation of the results (noted in Appendix A-1) was run through the ANN (see Figure 23).

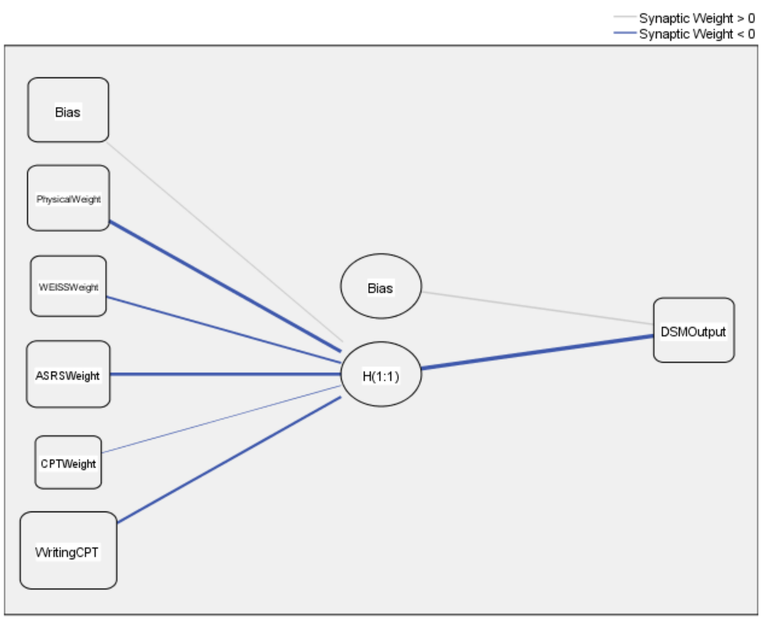
Case Processing Summary

		N	Percent
Sample	Training	30	66.7%
	Testing	15	33.3%
Valid		45	100.0%
Excluded		0	
Total		45	

Network Information

Input Layer	Covariates	1	Physical Weight
		2	WEISS Weight
		3	ASRS Weight
		4	CPT Weight
		5	Writing CPT
	Number of Units[a]		5
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		1
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	DSMOutput
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Figure 23. Final pass of correlation data for training the ADHD group model in SPSS.

Not surprisingly, the Physical screen (their degree of ADHD based on other comorbidity factors), ASRS screen (self-reporting questions for ADHD) and the Writing CPT showed the strongest connections (blue lines) to the DSM output of ADHD diagnosis. While the WEISS screen comparatively had a little less of a connection strength, it was still higher on the scale of importance than the Reaction-Based CPT, which is in line with the results of the CPT that was demonstrated earlier. Table 20 and Figure 24 captures the order importance of each ADHD test.

Table 20

Level of importance with covariates for the ADHD group training model

	Importance	Normalized Importance
Physical Weight	0.236	69.3%
WEISS Weight	0.130	38.4%
ASRS Weight	0.250	73.7%
CPT Weight	0.044	12.9%
WritingCPT	0.340	100%

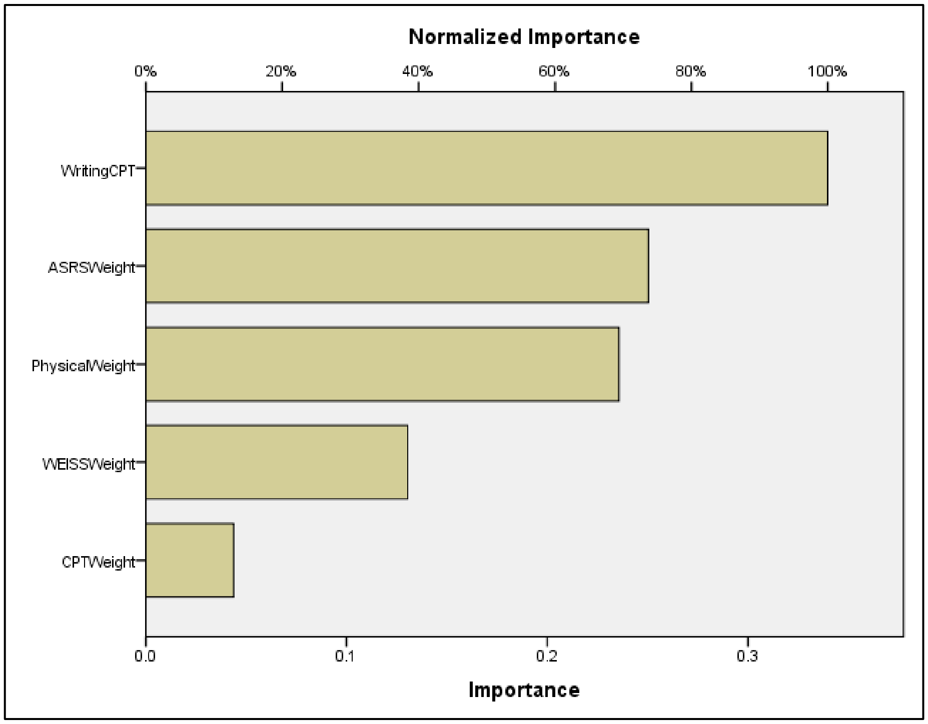


Figure 24. Level of importance with covariates for the ADHD group training model graphed.

Model Summary

Training	Sum of Squares Error	.103
	Relative Error	.007
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.013
	Relative Error	.003

Dependent Variable: DSMOutput

a. Error computations are based on the testing sample.

Figure 25. Relative error for training and testing samples for ADHD group.

It should be noted that the numbers above were on the model's third pass of retraining. The first pass started with a relative error of 0.125 for the training samples and 0.132 for the testing samples. The third pass ended with a relative error of 0.07 for the training samples and 0.013 for the testing samples (see Figure 25) before being again at

0.125 and 0.132 for the training and testing samples in a subsequent pass. Couple that with the Writing CPT being of the most importance and having the strongest synaptic weight (as indicated in Figures 23 and 24 above), and these statistics indicate that this pass was the best model for the training the behavior of diagnosing WLD in ADHD students, since it was the closest in relationship strength and the lowest in errors when calculating the weight to the DSM Output.

An interesting thing to note is that the correlation data from the control group (as per Appendix A-2) mirrored the model in connections, importance, error rate and the overall model, as shown in Table 21, Figure 26 and Figure 27:

Table 21

Level of importance with covariates for the Control group training model

	Importance	Normalized Importance
Physical Weight	0.267	83.1%
WEISS Weight	0.146	44.5%
ASRS Weight	0.233	71.1%
CPT Weight	0.025	7.6%
WritingCPT	0.328	100%

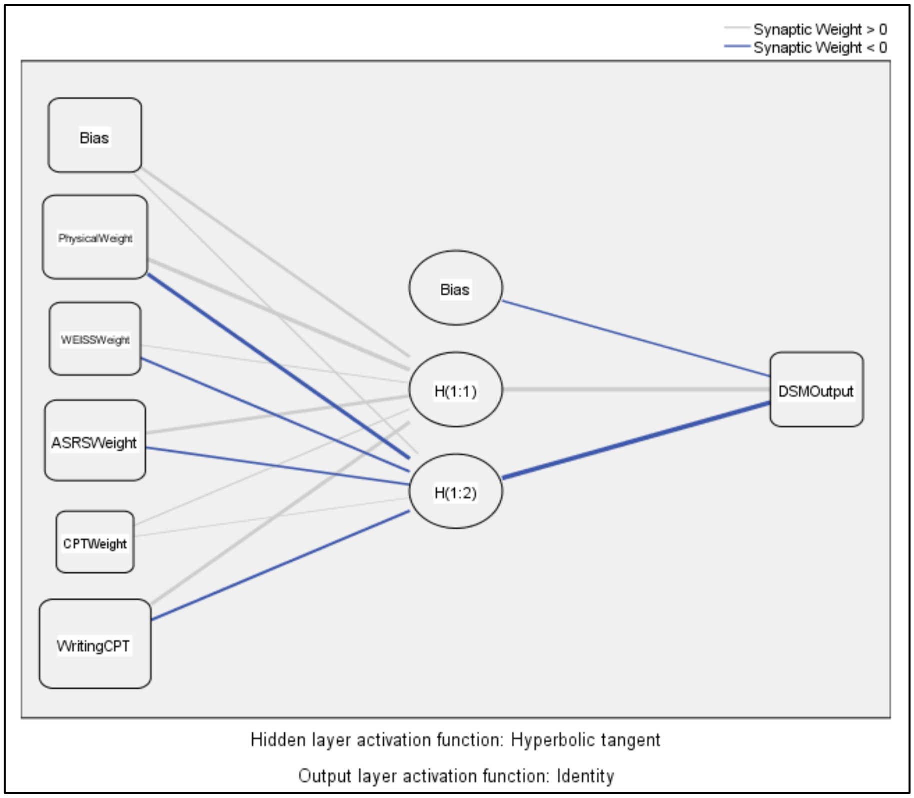


Figure 26. Connections of the covariates for control group training model.

Model Summary

Training	Sum of Squares Error	.021
	Relative Error	.001
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.070
	Relative Error	.005

Dependent Variable: DSM Output

a. Error computations are based on the testing sample.

Figure 27. Error rate of the covariates for control group training model.

Again, these numbers reinforced the consistency of the model for diagnosing ADHD and WLD in control students. However, this does not indicate if the covariates have a causal relationship with the ADHD and WLD classifier. For that, a casual model must be done on the covariates.

Causal Model of WLD

Because the presence of WLD in an ADHD student can be measured with the writing metrics stated in the methodology and there are correlations that have been illustrated in the results, a causal model (Boulanger, Seanosky, Clemens, Kumar, & Kinshuk, 2016) can be built that links these metrics.

To illustrate what can be done with the writing metrics using the data from ADHD students to match the WLD criteria, the following model can be generated in TETRAD V.

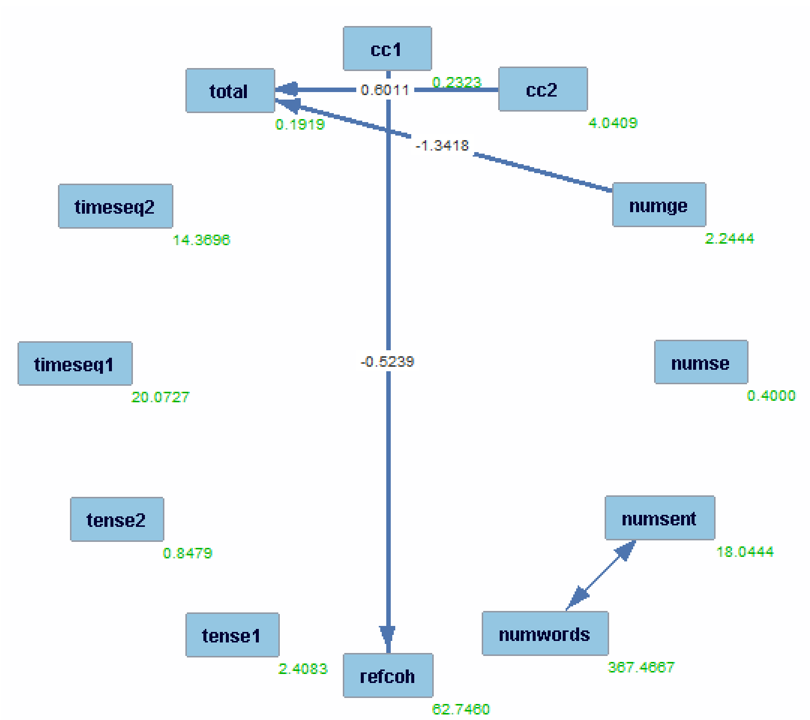


Figure 28. SEM IM from FCI Search over ADHD Student Writing Metrics.

The correlations between the metrics to the total WLD score is indicated in the diagram. The mean for the metric is indicated in green.

An FCI algorithm (Sprites, Glymour, & Scheines, 2002) is used on a Structural Equivalence Model (SEM) for an Instantiated Model (IM) since the model should account for hidden common causes between observed variables in the input. By running an FCI search, the model in Figure 28 indicates that the spelling, word count, sentence count, tense check, and time sequence are not a direct (or even indirect) cause of WLD based off the ADHD student data. However, topic flow (such as connective cohesion), grammar and cohesive adequacy were. Which is in line with the emphasis on written composition metrics introduced in previous research (Mitchnick, et al., 2017). Reviewing each metric to fine tune the direct path (ex. tense in relation to connective cohesion) would make a stronger causal case with those metrics in relation to the written language disorder classifier. For now, it is enough to say that those three metrics are the best fit for causal factors that affect written composition.

Doing the same process with the results for ADHD students overall to see the causing factors (or direct paths) with WLD, we get the following diagram (Figure 29):

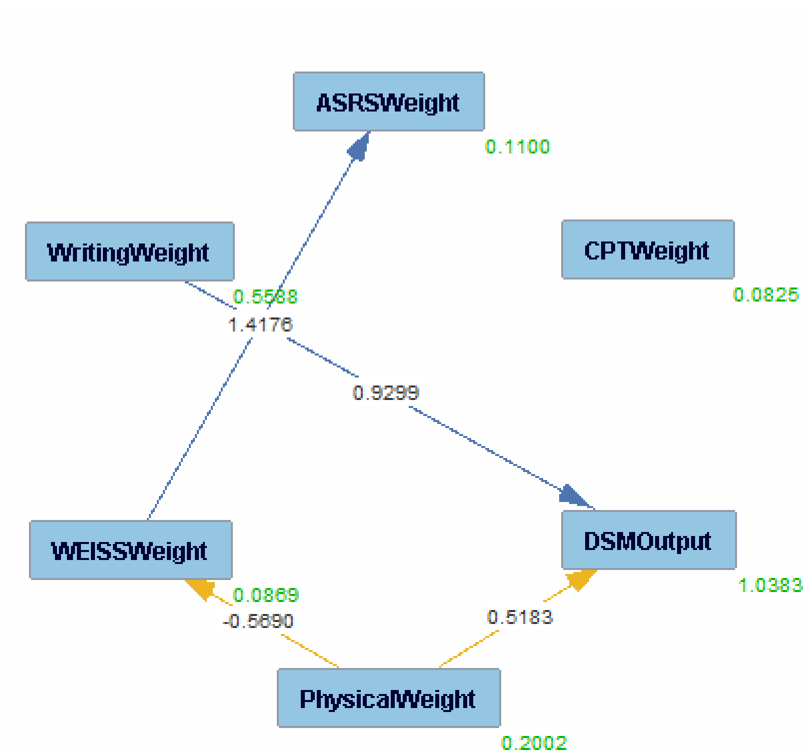


Figure 29. SEM IM from FCI Search over Actual ADHD data in relation to WLD. The correlations between the actual student screening data metrics to the total ADHD with WLD score is indicated in the diagram. The mean for the metric is indicated in green, while the yellow paths indicate the screen not being a directed path (i.e. certain indicator) of ADHD with WLD score.

Which not only has a high correlation between the writing data and WLD DSM criteria but yields significant coefficients as well (Table 22). One thing to note in the model is that the ASRS and the CPT screening data have no bearing on the WLD criteria, indicating that even if a student has ADHD, the two tests are not a strong indicator of it, or of determining WLD in the ADHD student.

Table 22

Covariance Matrix for FCI Search over Actual Screening Data (All Variables)

	DSMOutput	WritingWeight	CPTWeight	ASRSWeight	WEISSWeight	PhysicalWeight
DSMOutput	4.3283					
WritingWeight	-2.1415	2.3029				
CPTWeight	0	0	1.5823			
ASRSWeight	-0.5743	0	0	7.8581		
WEISSWeight	-0.4051	0	0	3.528	2.4886	
PhysicalWeight	0.712	0	0	-1.1079	-0.7815	1.3736

Running simulated data from this model, the model demonstrates the same pattern with the similar correlations (Figure 29), with a similar covariance matrix (Table 23).

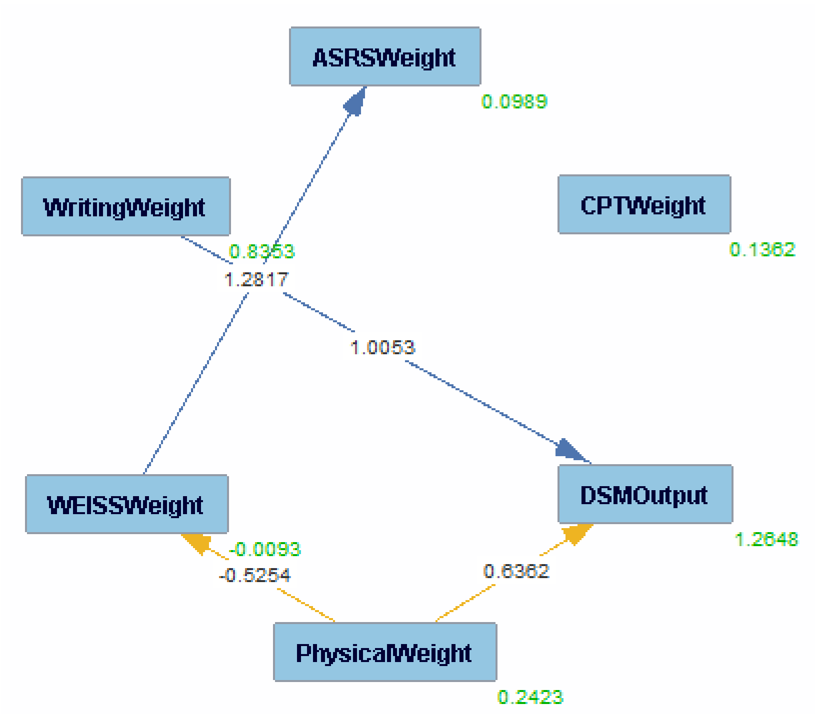


Figure 30. Estimated SEM from FCI Search over Simulated ADHD data in relation to WLD. The correlations between the simulated student screening data metrics to the total WLD score is indicated in the diagram. The mean for the metric is indicated in green. The yellow being undirected paths.

Table 23

Covariance Matrix for FCI Search over Simulated Screening Data (All Variables)

	DSMOutput	WritingWeight	CPTWeight	ASRSWeight	WEISSWeight	PhysicalWeight
DSMOutput	4.2276					
WritingWeight	1.323	1.3161				
CPTWeight	0	0	1.8366			
ASRSWeight	-0.7793	0	0	7.3571		
WEISSWeight	-0.608	0	0	2.8891	2.2542	
PhysicalWeight	1.1572	0	0	-1.2249	-0.9557	1.819

This similar pattern indicates that the model has a good fit. However, to determine if the model is truly a good fit, goodness-of-fit statistics (Table 24) must be run from the graphs (models) above. The minimally determined dataset of the variables over the 45 student datasets, is the most reliable model for causation. Its p-value is greater than 0.05, indicating that the model cannot be rejected, and the CFI score (which compares the target model to an independent or null model) is also very strong (greater than .90).

Table 24

Goodness-of-fit Values for ADHD and Control Group Data

Measure	Fit Value for ADHD Group	Fit Value for Control Group
Degrees of Freedom	11	11
Chi Square	7.4769	7.9883
P Value	0.7593	0.7144
BIC Score	-34.3964	-37.93
CFI	1.0086	1.0007

Finally, running the control data to determine the casual model for that group with the ADHD with WLD classifications, demonstrates a similar graph.

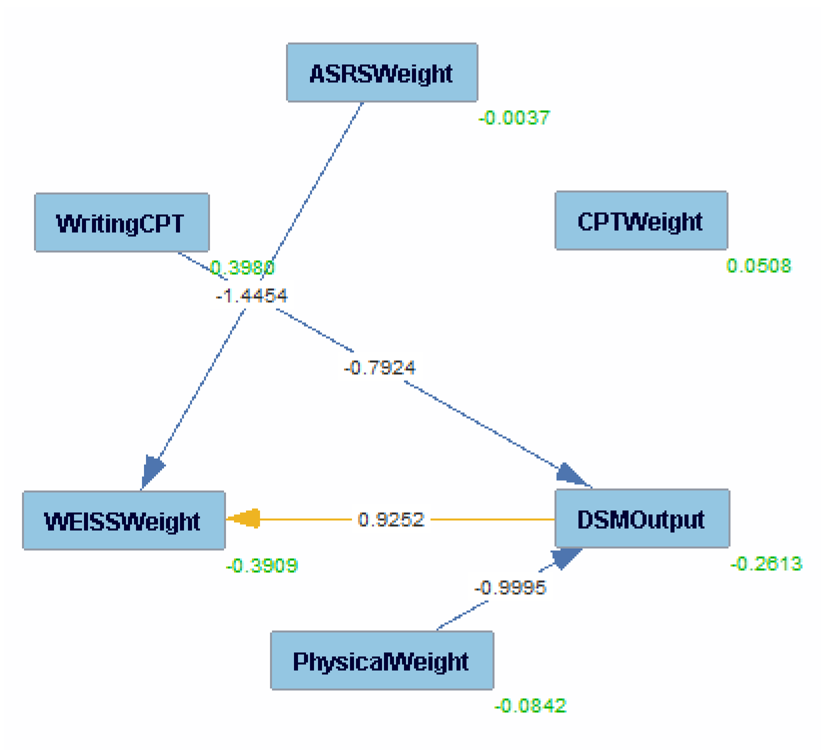


Figure 31. Estimated SEM from FCI Search over Simulated Control data in relation to the ADHD with WLD score. The correlations between the simulated student screening data metrics to the total ADHD with WLD score is indicated in the diagram. The mean for the metric is indicated in green. The yellow being undirected paths.

The only difference is that instead of a positive relationship, the relationship is negative. Which is correct in that an increase in the control group's written performance difficulties should not have an increase in matching with the ADHD with WLD classifier.

It is interesting to note that while the control model has negative correlations, the directed paths are similar, with a stronger correlation between the WritingCPT and the DSMOutput than any of the other covariates. This similar model structure and goodness-of-fit values even with the control data indicates that the casual model is a good fit, and that if considering screens in the future for testing, including written performance to measure written composition metrics would be a must, given the causal strength.

Chapter V will comment on the implications of these results for student learning, making recommendations for pedagogy and future research.

Chapter 5. Conclusions and Further Research

Having the statistical results of the experiment in hand, it is possible to answer the research question in full. Because the question's goal is to examine student's behavioural and learning performance to see if it is possible to identify measurable factors that contribute to ADHD with the WLD diagnosis to produce a more accurate outcome, the answer will be presented by examining the individual measuring factors. The causes and effects of each will be discussed in isolation, and the most significant ones will be covered in the recommendations.

Conclusions

In the sections below, each screen is examined to determine how it arises from the factors measured by the systems in this experiment. The validity of models will be kept in mind; the less-valid ones used only for speculation.

Self-Reporting Scales and Questionnaires

With any self-reporting tool, there is a degree of bias on the results as the student is responding to the questions with their own observations instead of a neutral party responding. Still, as many of the questionnaires were used as a starting point in obtaining a diagnosis, this information was still valid to collect, and great care had been done in the study to remove the external bias of wording that would allude to the ADHD, WLD or other behavioural and learning disorders.

Even with this precaution, the self-reporting scales and questionnaires for this study (Physical Questionnaire, ASRS and WEISS Questionnaire) were not as strong an indicator for the student having WLD or ADHD. Even the ADHD group (that were formally diagnosed with ADHD), did not (according to the test) fully display the conditions to be considered for ADHD in these questionnaires (i.e. had a relationship strength of ≥ 0.80 between the test and the ADHD classifier), inferring that the self-reporting scales and questionnaires on their own may not be an accurate testing tool to detect the presence of ADHD in students. With WLD, not having the WEISS Record Scale pick up on indicators for learning disorders inferred the same conclusion; that the self-reporting scales and questionnaires were not an accurate representation of detecting the presence of WLD alone. The significance tests showed this as well, with a $p > 0.05$ when comparing the ADHD group results to the ADHD markers in the WEISS Record. Though this is one of the standard tests when ruling out other mental health disorders, the results show that it may want to be run in conjunction with the other tests for a more accurate result (or be evaluated by a medical professional instead, due the bias that can occur in self-reporting).

Performance Testing

For performance testing, the Reaction-based CPT was even less of an indicator of ADHD being displayed in the participant's performance. Both groups performed rather consistently, which was more of a non-ADHD (control) characteristics, rather than the inattentive, hyperactive and impulsive characteristics that one would expect the ADHD group to display. While it was encouraged during the testing to not take any medication (including medication for ADHD, such as Concerta or Vyvanse), the participants not knowing the nature of this study, may not have seen the medication they would take for ADHD as a medication (since usually this is taken in the morning, and times recorded for work on the study indicated that many of the students started this test in the evening).

This factor may explain the performance of the ADHD group being similar to the control group, as the medication can help an ADHD participant focus and be less impulsive.

In order to test this theory, a set time during the day to complete the testing with an indication not to take medication of any kind 8 hours prior to the testing would need to be enforced. For this reason, even though the training model did not identify the Reaction-based CPT as a factor that could influence the ADHD outcome (i.e. the CPT having very weak connection as evidenced in the significance tests with a correlation coefficient (r) < 0.5 and a p-value > 0.05), it should not be discounted from the training model, until the above factor is controlled.

For the writing-based performance testing though, the connection was very strong and shed light into determining the relationship writing difficulties (and to the extent, WLD) had with ADHD. In addition to the strong connection in the training model, the measures for the written CPT were in line with the theoretical correlation analysis run against the DSM-V classification, validating the relationship. The correlation coefficient was > 0.5 for 34 of the ADHD participants and 27 of the control participants, meaning that the strength of relationship between the patient data and the DSM classifier was strong as well.

Analysis Models

With the ANN being used for this analysis to show the strength of the relationships on a non-linear path, it was expected that the all the standard tests (WEISS, ASRS and CPT) would have a strong relationship to the DSM classifier for ADHD with WLD. However, in the actual model it was discovered that checking for physical disorders that might rule out the presence of ADHD and WLD (Physical), ASRS and written performance (WritingCPT) had had the strongest relationships, inferring that it is likely that those with ADHD have a link to WLD as well. That said, this could not be confirmed, since running the same model for the control group had the same relationship strength has the ADHD group, when it was expected that it would not; enforcing the adage “correlation is not causation”.

To determine if there really is a link between ADHD and WLD, a casual model was used that showed that the ADHD group’s data had a positive strong correlation coefficient between writing and the DSM Output (indicating if there is a rise in writing difficulties, there is a rise in the output matching the ADHD and WLD classifier), while the control group showed a negative strong correlation coefficient (indicating if there is a increase in writing difficulties there is a not a rise or a decrease in the output matching the ADHD and WLD classifier). This means, while writing difficulties are a “cause” of the output of ADHD with WLD, it is the ADHD part specifically that causes the rise. If the control group increased in their writing difficulty, they would likely cause a rise in the WLD part of the classifier. Again, a study would have to be done on isolating WLD alone to determine this.

Future Research

The initial thesis based on this research detailed the process for gathering the information and the corresponding analysis when determining the prevalence of ADHD and WLD in those who have writing difficulties, including an initial proposed model of adult ADHD with WLD factors.

Practical Applications

Using this proposal model, a student could have a good start for getting the support they need based on the test results. For instance, if a student was showing they had a strong prevalence for ADHD and WLD, they could use these tests from this model to either get the diagnosis from a medical professional (for medication and/or behavioural/learning therapy) (CADDAC, 2019), or advocate for themselves on getting assistive technology and tools to support them with these disorders (such as speech-to-text tools when writing, extended completion dates in coursework, or mapping tools for organizing work) (Arbour, 2019).

With educators in the academic community, this model could be used on students to see where they are having difficulties, and how the educators in the academic community can use the student's diagnostic profile to apply for funding or curriculum changes at the university or school (Government of Alberta, 2019). This would help the university or school build a program that is more accommodating to students with these disorders. This model could be administered on students entering a program, or students currently in a program to determine the supports needed.

Although the model would require repeated testing and training to identify patterns that a medical professional could use for their field, this model could also be used at clinics or hospitals to identify mental health or learning disabilities in a patient, without the need to gather and analyze information from other sources first (Klykylo & Klykylo, 2008). This would save time in the medical professional diagnosing the patient (since they would have a learning and behavioral profile already) and it would also save time in the patient having to collect the information for a diagnosis (since the information would already be collected).

Other Areas of Research

There are other useful statistics that could branch this research into other directions, such as age determination in the study, genetic predisposition (family history) studies, gender studies and comorbidity studies. The data collected, the software used to collect it, and the model could also spark other research into the support and/or treatment of adult ADHD or other mental health disorders, and WLD or other learning disorders. For example, if the data could be analyzed in such a way as to be able to show the cause of the factors that confirmed the presence of WLD only, further analysis could be done on mitigating the influence of those factors and how that mitigation could neutralize the exacerbation of WLD in the student.

The research could also be a model to determine the exclusive or inclusive nature of mental health disorders with learning disorder. For example, there have been research studies on autism and reading disorders separately, but not many studies on the two disorders together. By using this model as a base for that research and pinpointing on where the student drops off in their assignments, or where they experience difficulty, educators can learn about the types of learning styles that can work the best for students with mental health and/or learning disorders.

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Appendix A: Additional Tables

Table 3 Results of the studies included in the meta-analysis

	Prevalence defined by DSM–IV criteria, %				Prevalence defined by criteria other than DSM–IV, %			
	Total[a]	I[a]	HI	Comb.	Total[a]	I[a]	HI	Comb.
Murphy & Barkley[25]	4.7	1.3	2.5	0.9	No data available			
Heiligenstein *et al*[28]	4	2.24[b]	0.88	0.88	11	3.74[b]	3.96	3.30
					Reduced number of symptoms required (4)			
DuPaul *et al*[27]								
Italy	1.01	0.51[b]	0.51	0	42.31	8.82[b]	23.42	98.68
New Zealand	2.81	0.47[b]	2.34	0	36.06	9.50[b]	17.08	9.48
USA	3.39	0.75[b]	2.15	0.5	26.91	4.97[b]	13.90	7.15
					Reduced number of symptoms required (3)			
Kooij *et al*[19]	1	0.2	0.5	0.3	2.5	0.3	1.2	1.0
					Reduced number of symptoms required (4)			
Faraone & Biederman[34]	2.9	0.7	1.1	1.1	16.4	5.8	3.7	6.9
					'Broad' ADHD[c]			
Almeida Montes *et al*[29]	5.37				No data available			

ADHD, attention-deficit hyperactivity disorder; Comb., combined subtype; HI, hyperactive–impulsive subtype; I, inattentive subtype.
a. Total: all subtypes of ADHD pooled (inattentive subtype, hyperactive–impulsive subtype, combined subtype).
b. Our calculation from data given in the original article.
c. Referred as screening diagnosis in the original article.

Figure 1. Table of demographic meta-analysis prevalence to ADHD defined by the DSM-IV criteria. Reprinted from *Prevalence and correlates of adult attention-deficit hyperactivity disorder: meta-analysis*, by The British Journal of Psychiatry, March 2009, retrieved from https://doi.org/10.1192/bjp.bp.107.048827 Copyright 2009 by The British Journal of Psychiatry.

Table 4
Pooled effect sizes and meta-analytic parameters

	N studies	*N* patients	*d*	CI low	CI upper	*z* (*d*)	*P* (*z*)	χ^2	*P* (χ^2)	TAU	I^2
Verbal intelligence	12	863	−.27	−.43	−.11	−3.34	.00	13.5	.26	.014	19
Executive functions	7	464	−.21	−.46	.03	−1.70	.09	9.5	.14	.039	37
Visual/verbal fluency	7	527	−.52	−.83	−.20	−3.23	.00	17.4	.00	.113	65
Visual/figural problem solving	8	762	−.26	−.40	−.11	−3.45	.00	4.0	.78	.000	0
Abstract problem solving; working memory	12	952	−.51	−.64	−.37	−7.40	.00	10.8	.46	.000	0
Simple attention	22	1537	−.38	−.55	−.22	−4.50	.00	47.6	.00	.080	56
Sustained attention	13	963	−.52	−.65	−.39	−7.79	.00	11.1	.52	.000	0
Focused attention	22	1493	−.55	−.68	−.42	−8.31	.00	28.3	.13	.023	26
Verbal memory	8	546	−.56	−.79	−.37	−6.14	.00	6.2	.52	.000	0
Figural memory	8	541	−.18	−.35	.00	−1.93	.05	7.5	.38	.005	7

d, pooled weighted effect size; CI low/upper, confidence interval (*d*); *z*, *z*-value; χ^2, χ^2 for heterogeneity; TAU, heterogeneity correction for random effects model; I^2, percentage of heterogeneity due to study differences. See Formulas 1–10 for all parameters.

Figure 2. Table of functional domains that measured performance for ADHD groups compared to control groups. Reprinted from *Neuropsychological performance in adult attention-deficit hyperactivity disorder: Meta-analysis of empirical data* by Archives of Clinical Neuropsychology, August 1, 2005, retrieved from

https://doi.org/10.1016/j.acn.2005.04.005

Table A-1

Scores for ADHD Students with WLD in Data Collection

Student	Physical Weighted	WEISS Weighted	ASRS Weighted	CPT Weighted	Writing CPT Weighted	DSM Output
ADHD1	0	0.06625	0.068	0.085062	0.327522	0.546834
ADHD2	0.53	0	0.068	0.086084	0.160229	0.844313
ADHD3	0	0.33125	0.2	0.078992	0.593876	1.204118
ADHD4	0	0.265	0.134	0.083909	0.479549	0.962457
ADHD5	0	0.06625	0.134	0.090723	0.48048	0.771453
ADHD6	0.53	0.06625	0.134	0.089291	0.606783	1.426323
ADHD7	0	0	0	0.086979	0.782381	0.869359
ADHD8	0	0.1325	0.134	0.089937	0.279906	0.636343
ADHD9	0.53	0	0	0.085126	0.578503	1.193628
ADHD10	0.53	0	0.066	0.085661	0.706969	1.38863
ADHD11	0	0.33125	0.2	0.073832	0.619399	1.224481
ADHD12	0.53	0.06625	0.2	0.078519	0.401018	1.275788
ADHD13	0.53	0	0.134	0.087533	0.965549	1.717082
ADHD14	0	0.1325	0.2	0.089682	0.515123	0.937305
ADHD15	0	0.1325	0.2	0.079261	0.575097	0.986858
ADHD16	0	0	0.134	0.072899	0.452552	0.659451
ADHD17	0	0	0.134	0.082604	0.598281	0.814884
ADHD18	0	0.1325	0.068	0.080516	0.867585	1.1486
ADHD19	0.53	0	0.2	0.07866	0.631562	1.440223
ADHD20	0	0.06625	0.068	0.088057	0.442805	0.665111
ADHD21	0.53	0	0.068	0.073007	0.538095	1.209102
ADHD22	0	0.06625	0.2	0.091899	0.86788	1.226029
ADHD23	0	0.06625	0	0.073486	0.585482	0.725218
ADHD24	0	0.06625	0.2	0.08335	0.365167	0.714767
ADHD25	0.53	0.06625	0.066	0.101652	0.349963	1.113866
ADHD26	0.53	0.1325	0.2	0.068556	0.493876	1.424932
ADHD27	0.53	0.19875	0.2	0.084895	0.422417	1.436062

ADHD28	0	0.1325	0.134	0.076938	0.49632	0.839758
ADHD29	0.53	0	0.2	0.0784	0.711239	1.519639
ADHD30	0	0.19875	0.2	0.089571	0.486946	0.975267
ADHD31	0.53	0.06625	0.068	0.073287	0.468479	1.206016
ADHD32	0.53	0	0.068	0.07815	0.417429	1.093579
ADHD33	0	0.06625	0.2	0.092082	0.649719	1.008051
ADHD34	0	0	0	0.077596	0.409625	0.487221
ADHD35	0	0	0	0.078488	0.388665	0.467153
ADHD36	0.53	0	0.068	0.077924	0.539093	1.215017
ADHD37	0	0.1325	0.134	0.073497	0.563753	0.903749
ADHD38	0	0.265	0.134	0.081266	0.476243	0.95651
ADHD39	0.53	0.06625	0	0.08812	0.292931	0.9773
ADHD40	0	0	0	0.087023	1.203957	1.29098
ADHD41	0	0.1325	0	0.084189	0.490029	0.706719
ADHD42	0	0	0	0.072564	0.6804	0.752964
ADHD43	0	0.19875	0.134	0.079195	0.6774	1.089345
ADHD44	0.53	0	0	0.080874	0.889144	1.500018
ADHD45	0	0.265	0.2	0.091342	0.616157	1.172499

Table A-2

Scores for Control Group with WLD in Data Collection

Student	Physical Weighted	WEISS Weighted	ASRS Weighted	CPT Weighted	Writing CPT Weighted	DSM Output
CNTL1	0.53	0.265	0.068	0.075574	0.401834	1.340408
CNTL2	0	0	0	0.074777	0.484954	0.559731
CNTL3	0.53	0	0	0.088055	0.564277	1.182331
CNTL4	0.53	0	0.134	0.08752	0.370994	1.122514
CNTL5	0	0	0.068	0.072808	0.836244	0.977053
CNTL6	0	0	0.068	0.088305	0.254162	0.410466
CNTL7	0	0.06625	0.066	0.079688	0.454124	0.666062
CNTL8	0.53	0	0	0.079031	0.625805	1.234836
CNTL9	0	0	0	0.085006	0.817966	0.902972
CNTL10	0.53	0	0	0.081046	0.567081	1.178126

CNTL11	0.53	0	0	0.075046	0.469563	1.074609
CNTL12	0	0	0	0.076383	0.358676	0.435059
CNTL13	0.53	0.06625	0	0.077436	0.562881	1.236567
CNTL14	0	0	0	0.07068	0.304414	0.375093
CNTL15	0	0	0	0.090425	0.300922	0.391347
CNTL16	0	0	0.068	0.071334	0.213148	0.352482
CNTL17	0	0.19875	0.134	0.092702	0.437122	0.862574
CNTL18	0	0	0.068	0.087124	0.456426	0.61155
CNTL19	0.53	0	0	0.078379	0.407591	1.01597
CNTL20	0	0.06625	0	0.073053	0.639168	0.778472
CNTL21	0	0	0	0.080907	1.093181	1.174088
CNTL22	0.53	0.06625	0	0.074782	0.86262	1.533651
CNTL23	0.53	0	0	0.072648	0.643618	1.246267
CNTL24	0	0	0	0.079245	0.443594	0.522839
CNTL25	0.53	0	0	0.08519	0.709339	1.32453
CNTL26	0.53	0	0	0.089721	0.35988	0.979601
CNTL27	0	0	0.134	0.0857	0.565738	0.785438
CNTL28	0	0	0	0.073614	0.606787	0.680401
CNTL29	0.53	0	0.068	0.083524	0.421637	1.103161
CNTL30	0.53	0	0	0.079317	0.792203	1.40152
CNTL31	0.53	0	0	0.071033	0.681967	1.283001
CNTL32	0.53	0.1325	0	0.07242	0.604224	1.339144
CNTL33	0	0	0	0.091993	0.643599	0.735592
CNTL34	0	0	0	0.081986	0.505284	0.587271
CNTL35	0	0	0	0.085541	0.388215	0.473756
CNTL36	0.53	0	0.068	0.076106	0.395491	1.069597
CNTL37	0	0	0.068	0.077292	0.565506	0.710797
CNTL38	0.53	0	0	0.07566	0.675487	1.281146
CNTL39	0.53	0	0	0.085021	0.503489	1.11851
CNTL40	0	0.06625	0	0.076753	0.606703	0.749706
CNTL41	0	0.06625	0	0.071001	0.45031	0.587561
CNTL42	0	0	0	0.077535	0.458199	0.535734
CNTL43	0	0.1325	0.134	0.077753	0.61711	0.961363
CNTL44	0	0	0	0.07554	0.404665	0.480205

CNTL45	0	0.06625	0.066	0.088207	0.40935	0.629807
CNTL46	0.53	0	0	0.088028	0.565216	1.183244
CNTL47	0.53	0	0	0.083712	0.542314	1.156026
CNTL48	0	0	0	0.069346	0.396783	0.46613
CNTL49	0.53	0	0	0.080745	0.42696	1.037705
CNTL50	0	0.06625	0	0.073909	0.922534	1.062693
CNTL51	0	0	0.068	0.075144	0.608192	0.751335
CNTL52	0.53	0	0	0.074855	0.832529	1.437384
CNTL53	0.53	0.1325	0.134	0.088547	0.318649	1.203695
CNTL54	0	0	0	0.07313	0.866031	0.939161
CNTL55	0.53	0.1325	0.068	0.077408	0.580932	1.38884
CNTL56	0	0	0	0.078761	0.508324	0.587085
CNTL57	0.53	0.06625	0	0.073871	0.585684	1.255805
CNTL58	0	0	0	0.085408	0.442522	0.527931
CNTL59	0	0.19875	0.2	0.074458	0.684204	1.157411
CNTL60	0.53	0.19875	0	0.078958	0.658003	1.465711
CNTL61	0.53	0.06625	0	0.080527	0.586832	1.26361
CNTL62	0.53	0	0	0.076772	0.357422	0.964194
CNTL63	0.53	0.06625	0	0.087704	0.678817	1.362771
CNTL64	0	0.06625	0.134	0.080269	0.612763	0.893281
CNTL65	0	0	0	0.088865	0.418969	0.507834

Table A-3

Individual Scores for CPT

Student	Number of Correct Responses	Omission Errors	Commission Errors	Reaction Time (ms)
ADHD1	172	28	0	0.12530814
ADHD2	163	37	2	0.127420245
ADHD3	177	23	9	0.081459887
ADHD4	152	48	8	0.107544079
ADHD5	147	53	17	0.128116327
ADHD6	178	22	8	0.134453933
ADHD7	158	42	5	0.127393038

ADHD8	155	45	7	0.139184516
ADHD9	141	59	14	0.104628369
ADHD10	128	72	24	0.092303906
ADHD11	174	26	5	0.061662178
ADHD12	157	43	7	0.082097452
ADHD13	159	41	7	0.127164151
ADHD14	147	53	15	0.125908163
ADHD15	158	42	0	0.096303797
ADHD16	152	48	1	0.062995395
ADHD17	193	7	12	0.095018653
ADHD18	171	29	12	0.084578363
ADHD19	167	33	5	0.085801198
ADHD20	151	49	10	0.125282781
ADHD21	166	34	3	0.060536747
ADHD22	150	50	9	0.145996
ADHD23	155	45	0	0.067431613
ADHD24	153	47	13	0.097250327
ADHD25	134	66	24	0.17226194
ADHD26	170	30	0	0.042780588
ADHD27	165	35	30	0.079473333
ADHD28	158	42	16	0.060689241
ADHD29	162	38	12	0.074000617
ADHD30	160	40	14	0.12685625
ADHD31	161	39	1	0.064936646
ADHD32	139	61	2	0.087751799
ADHD33	200	0	30	0.115410726
ADHD34	158	42	8	0.075981646
ADHD35	147	53	2	0.089440136
ADHD36	143	57	3	0.08512028
ADHD37	160	40	3	0.0629825
ADHD38	137	63	21	0.074832117
ADHD39	164	36	12	0.122597561
ADHD40	172	28	16	0.111112791
ADHD41	136	64	9	0.107447059

ADHD42	156	44	1	0.061321795
ADHD43	149	51	6	0.08697651
ADHD44	173	27	2	0.101371098
ADHD45	180	20	30	0.11170871
CNTL1	166	34	1	0.076368675
CNTL2	162	38	2	0.070887037
CNTL3	175	25	10	0.125272571
CNTL4	142	58	29	0.094099296
CNTL5	166	34	2	0.061040361
CNTL6	173	27	18	0.114522543
CNTL7	142	58	12	0.080440845
CNTL8	154	46	4	0.089153247
CNTL9	171	29	1	0.123531579
CNTL10	151	49	7	0.094727815
CNTL11	160	40	3	0.07073125
CNTL12	149	51	3	0.077416779
CNTL13	153	47	1	0.085679739
CNTL14	148	52	1	0.051897973
CNTL15	152	48	11	0.135623026
CNTL16	169	31	0	0.056668047
CNTL17	146	54	22	0.130510274
CNTL18	121	79	30	0.090621488
CNTL19	157	43	0.012	0.079896815
CNTL20	159	41	0.003	0.062267296
CNTL21	158	42	0.033	0.071536709
CNTL22	138	62	0.0045	0.069408696
CNTL23	170	30	0.0015	0.061741765
CNTL24	155	45	0	0.096223871
CNTL25	142	58	0.0165	0.109450704
CNTL26	181	19	0.0105	0.138102762
CNTL27	168	32	0.009	0.119499405
CNTL28	156	44	0	0.068069231
CNTL29	149	51	0.012	0.105622148
CNTL30	158	42	0.003	0.093584177

CNTL31	154	46	0	0.055166234
CNTL32	165	35	0	0.062098182
CNTL33	160	40	0.015	0.14496625
CNTL34	131	69	0.0135	0.096432061
CNTL35	99	101	0.0285	0.099205051
CNTL36	138	62	0.0015	0.07902971
CNTL37	165	35	0.006	0.080458788
CNTL38	156	44	0.0045	0.073798718
CNTL39	175	25	0	0.125104
CNTL40	164	36	0.0045	0.079262805
CNTL41	166	34	0.0015	0.053506024
CNTL42	177	23	0.0015	0.086174576
CNTL43	157	43	0.006	0.082765605
CNTL44	164	36	0.0015	0.076202439
CNTL45	127	73	0.045	0.096037008
CNTL46	162	38	0.0105	0.129638889
CNTL47	199	1	0.027	0.091560302
CNTL48	144	56	0	0.046731944
CNTL49	151	49	0.012	0.091722517
CNTL50	154	46	0.003	0.066542857
CNTL51	161	39	0.0045	0.071218012
CNTL52	152	48	0	0.074273684
CNTL53	155	45	0.006	0.136733548
CNTL54	158	42	0.0015	0.064149367
CNTL55	151	49	0.0105	0.07654106
CNTL56	146	54	0.015	0.078805479
CNTL57	162	38	0.003	0.066354938
CNTL58	156	44	0	0.127041026
CNTL59	200	0	0.0015	0.070787624
CNTL60	163	37	0.0105	0.084290798
CNTL61	134	66	0.015	0.087635075
CNTL62	177	23	0.006	0.077859887
CNTL63	166	34	0.0105	0.128019277
CNTL64	166	34	0.0135	0.087842771

CNTL65	147	53	0.0165	0.12782585

Table A-4

Individual Scores for Writing CPT

Student	DESWC	DESSC	SE	GE	WRDPRP3s	SYNTEMP	CNCTemp	CNCTempX	LSASS1	SYNLE	PCREFz
ADHD1	0.07406	0.075	0	0.045	0	0.100463	0.089406	0.063861	0.0792	0.065993	0.01354
ADHD2	0.01079	0.015	0	0	0	0.084375	0	0	0.0648	0.074993	0.046762
ADHD3	0.113052	0.13	0	0.09	0	0.0945	0.185468	0.167336	0.0828	0.103838	0.132778
ADHD4	0.094659	0.095	0	0.09	0	0.087525	0.046634	0.116582	0.126	0.091193	0.14046
ADHD5	0.124087	0.175	0	0.09	0	0.082688	0.071145	0.088933	0.08955	0.047565	0.12081
ADHD6	0.074796	0.115	0.225	0.225	0	0.0972	0.059018	0.105384	0.0702	0.08217	0.069905
ADHD7	0.232725	0.16	0	0.045	0.316125	0.094388	0.161222	0.060969	0.1359	0.12024	0.122286
ADHD8	0.019373	0.035	0	0	0	0.1125	0.056961	0.162746	0.0612	0.032153	0.038413
ADHD9	0.086076	0.08	0.225	0.09	0	0.1125	0.064103	0.07326	0.1107	0.12798	0.101683
ADHD10	0.117711	0.105	0	0.09	0.312488	0.092813	0.206249	0.093748	0.09945	0.081428	0.110317
ADHD11	0.168719	0.125	0.225	0.09	0	0.084375	0.104652	0.093439	0.0774	0.1611	0.017349
ADHD12	0.076022	0.075	0	0.09	0	0.084375	0.014517	0.041477	0.12645	0.1125	0.122286
ADHD13	0.105695	0.12	0.9	0.09	0.174	0.080663	0.052205	0.074578	0.0666	0.09468	0.029635
ADHD14	0.089264	0.075	0	0	0	0.084375	0.098901	0.158946	0.153	0.142493	0.151952
ADHD15	0.064005	0.06	0	0.18	0	0.102263	0.034484	0.098524	0.15345	0.217508	0.154762
ADHD16	0.101035	0.09	0	0.09	0	0.099225	0.098303	0.062415	0.1197	0.045	0.132381
ADHD17	0.090736	0.05	0	0.09	0.101363	0.100013	0.109458	0.156369	0.1827	0.06975	0.15754
ADHD18	0.160872	0.175	0	0.09	0.800288	0.104175	0.075456	0.068599	0.03915	0.061718	0.031381
ADHD19	0.130218	0.15	0.225	0.135	0	0.100913	0.059324	0.121063	0.0684	0.110993	0.068651
ADHD20	0.022561	0.03	0	0	0	0.07875	0.097826	0.139751	0.1962	0.097493	0.157429
ADHD21	0.091471	0.095	0	0.27	0	0.100013	0.108581	0.10341	0.0774	0.068693	0.081905
ADHD22	0.13733	0.13	0	0.405	0.401775	0.09675	0.120537	0.068876	0.10935	0.058838	0.07873
ADHD23	0.110845	0.105	0	0.225	0.08295	0.084375	0.049779	0.071113	0.1296	0.1125	0.113063
ADHD24	0.028202	0.03	0	0.045	0	0.10125	0.039132	0.167702	0.11745	0.0675	0.08
ADHD25	0.077248	0.065	0	0.135	0	0.1125	0.042858	0	0.0702	0.093465	0.05181
ADHD26	0.081172	0.075	0	0	0	0.100463	0.108761	0.213641	0.08955	0.109508	0.136492
ADHD27	0.036049	0.045	0	0.09	0	0.084375	0.12245	0.087461	0.0936	0.10251	0.12081

ADHD28	0.083869	0.055	0	0.09	0	0.09	0.19737	0.037594	0.12285	0.094095	0.148333
ADHD29	0.089755	0.085	0.225	0.135	0.2049	0.084375	0.086067	0.245899	0.0702	0.04896	0.041952
ADHD30	0.078719	0.08	0	0.135	0	0.07875	0.084114	0.060081	0.0954	0.15048	0.139206
ADHD31	0.096866	0.095	0	0	0	0.1062	0.056961	0.09765	0.20475	0.05211	0.158016
ADHD32	0.104223	0.125	0	0.09	0	0.091463	0.063531	0.075632	0.06885	0.09	0.064317
ADHD33	0.075041	0.08	0	0.135	0.2451	0.09	0.117648	0.084034	0.13725	0.104063	0.135048
ADHD34	0.108638	0.115	0	0	0	0.089438	0.071105	0.043534	0.10755	0.09684	0.12646
ADHD35	0.085586	0.085	0	0	0	0.09495	0.077364	0.073678	0.10215	0.107213	0.09381
ADHD36	0.075041	0.095	0	0.045	0	0.100013	0.22059	0.084034	0.1494	0.073418	0.155825
ADHD37	0.082888	0.09	0	0.09	0	0.105863	0.146448	0.152158	0.1647	0.126248	0.085683
ADHD38	0.022316	0.025	0.225	0.135	0	0.1125	0.098901	0.070644	0.0495	0.0675	0.075571
ADHD39	0.025259	0.02	0	0.09	0	0.1125	0	0	0.0774	0.07875	0.138556
ADHD40	0.082153	0.09	0.225	0.18	1.119413	0.1026	0.094032	0.153521	0.05355	0.062505	0.066778
ADHD41	0.095886	0.12	0.225	0.135	0	0.09045	0.057546	0.016444	0.0522	0.059063	0.055873
ADHD42	0.179755	0.175	0.225	0.045	0	0.084375	0.165758	0.07893	0.10845	0.099653	0.098079
ADHD43	0.074305	0.095	0.225	0.18	0	0.103163	0.089109	0.106084	0.1458	0.09711	0.138873
ADHD44	0.078229	0.055	0.9	0.045	0.117563	0.10125	0.070533	0.020154	0.11655	0.049095	0.09319
ADHD45	0.097847	0.095	0	0.225	0.187988	0.096863	0.090225	0.096673	0.08775	0.080528	0.083159
CNTL1	0.07688	0.056842	0	0.135	0	0.102263	0.121257	0.035928	0.1341	0.069368	0.0125
CNTL2	0.087008	0.099474	0	0	0	0.104063	0.083336	0.126984	0.11475	0.086783	0.195667
CNTL3	0.126368	0.09	0.18	0.045	0.046826	0.103163	0.114755	0.087432	0.126	0.139748	-0.01433
CNTL4	0.070895	0.113684	0	0	0.166989	0.097875	0.058442	0.097404	0.06885	0.089055	-0.07617
CNTL5	0.104962	0.104211	0	0	0.902263	0.093713	0.039474	0.092106	0.10035	0.07569	0.035833
CNTL6	0.07688	0.09	0	0	0	0.100013	0.040419	0.053892	0.0603	0.0675	-0.01833
CNTL7	0.097136	0.123158	0	0.135	0.12186	0.08325	0.031991	0.042654	0.08865	0.057105	0.060167
CNTL8	0.116471	0.142105	0	0.135	0.15246	0.104738	0.106718	0.071148	0.09585	0.072743	0.161667
CNTL9	0.117391	0.118421	0.18	0.045	0.403354	0.096075	0.079412	0.105882	0.12015	0.0729	0.176167
CNTL10	0.151918	0.118421	0	0.18	0	0.110138	0.095454	0.100002	0.07425	0.1143	0.105667
CNTL11	0.092992	0.09	0	0.09	0	0.093713	0.033417	0.044556	0.1503	0.084083	0.1905
CNTL12	0.069744	0.094737	0	0.045	0	0.094725	0.133664	0.138612	0.07515	0.09675	-0.08417
CNTL13	0.094373	0.080526	0	0.09	0	0.105525	0.076829	0.102438	0.1584	0.119115	0.215167
CNTL14	0.081023	0.080526	0	0	0.146109	0.091463	0.076703	0.136362	0.05355	0.046328	-0.14833
CNTL15	0.083555	0.094737	0	0	0	0.0918	0.086778	0.082644	0.06075	0.063	-0.006
CNTL16	0.068133	0.123158	0	0.045	0	0.1035	0.091215	0.06081	0.0621	0.062303	-0.2215

CNTL17	0.109795	0.099474	0	0.045	0	0.09	0.113207	0.025158	0.0963	0.115718	0.114833
CNTL18	0.066292	0.066316	0	0.045	0	0.082238	0.171873	0.166668	0.063	0.147848	0.036
CNTL19	0.095294	0.085263	0	0.045	0	0.105863	0.097826	0.043476	0.10665	0.13626	0.039167
CNTL20	0.11509	0.123158	0.18	0.18	0.051429	0.0855	0.126	0.072	0.10125	0.118553	0.030667
CNTL21	0.070665	0.108947	0.18	0.045	1.2564	0.089438	0.073292	0.058632	0.081	0.081203	-0.02017
CNTL22	0.085627	0.085263	0.72	0.18	0	0.099225	0.024192	0.064518	0.0972	0.076253	0.165167
CNTL23	0.092302	0.099474	0	0.135	0.128263	0.092813	0.078552	0.074814	0.12735	0.099653	0.263667
CNTL24	0.117621	0.118421	0	0.045	0	0.096075	0.096867	0.093936	0.12645	0.1521	-0.025
CNTL25	0.083555	0.056842	0	0.135	0	0.092025	0.099176	0.181818	0.1476	0.221243	0.296333
CNTL26	0.078951	0.080526	0	0.045	0	0.087863	0.052479	0.122448	0.08235	0.113828	0.003
CNTL27	0.100818	0.094737	0	0.135	0.234823	0.085838	0.113013	0.095892	0.0765	0.048375	0.062667
CNTL28	0.010358	0.009474	0	0	0	0.1125	0	0.266664	0.20385	0.045	0.475833
CNTL29	0.072737	0.052105	0	0.135	0	0.09	0.028481	0.037974	0.10575	0.102263	0.1565
CNTL30	0.083095	0.075789	0	0.135	0.427397	0.104963	0.062325	0.04986	0.1143	0.08298	0.331333
CNTL31	0.084706	0.085263	0	0.135	0.209623	0.0927	0.146741	0.06522	0.12465	0.09	0.229
CNTL32	0.093683	0.075789	0.18	0.09	0	0.097538	0.044226	0.07371	0.1233	0.144855	0.195833
CNTL33	0.105652	0.104211	0.36	0.09	0	0.080325	0.078431	0.117648	0.11475	0.1125	0.028333
CNTL34	0.098056	0.099474	0.18	0.045	0	0.098438	0.073944	0.05634	0.11925	0.07821	0.087
CNTL35	0.075959	0.066316	0	0.135	0	0.095175	0.027275	0.090912	0.0981	0.080348	0.049833
CNTL36	0.084476	0.099474	0	0.045	0	0.095625	0.159399	0.01635	0.09585	0.070718	0.0655
CNTL37	0.06376	0.071053	0.18	0.045	0	0.10845	0.097475	0.194946	0.15255	0.0495	0.0845
CNTL38	0.107724	0.080526	0.18	0.09	0	0.0738	0.08654	0.03846	0.1863	0.128385	0.279167
CNTL39	0.076189	0.080526	0	0.18	0	0.1125	0.054383	0.07251	0.1314	0.062213	0.162667
CNTL40	0.114859	0.113684	0	0.225	0.103063	0.092925	0.063126	0.096192	0.09405	0.095625	0.125
CNTL41	0.089309	0.094737	0	0.045	0.066266	0.0918	0.104382	0.077322	0.0963	0.046125	0.122667
CNTL42	0.097596	0.085263	0.18	0.045	0	0.0927	0.031838	0.212262	0.10935	0.060008	-0.0655
CNTL43	0.073657	0.080526	0.18	0.09	0	0.098438	0.070313	0.01875	0.1674	0.084713	0.279
CNTL44	0.070665	0.071053	0	0.045	0	0.104513	0.073292	0.058632	0.1269	0.097493	0.101833
CNTL45	0.055013	0.09	0	0.18	0.107589	0.087525	0.056484	0.100416	0.05175	0.063945	-0.03467
CNTL46	0.118082	0.151579	0.18	0	0	0.076163	0.140351	0.128652	0.0801	0.098438	0.073333
CNTL47	0.086547	0.075789	0	0.18	0	0.097538	0.071807	0.063828	0.1404	0.164543	0.123833
CNTL48	0.104501	0.085263	0.18	0	0.113271	0.072788	0.069386	0.118944	0.0468	0.114998	-0.17117
CNTL49	0.057315	0.061579	0	0	0	0.1125	0.054216	0.048192	0.1458	0.091733	0.219333
CNTL50	0.070435	0.080526	0.18	0.045	0.504206	0.09495	0.176472	0.19608	0.1089	0.068828	0.183

CNTL51	0.104041	0.123158	0	0.135	0.227571	0.08775	0.089604	0.092922	0.09945	0.052785	0.114
CNTL52	0.10335	0.127895	0.54	0.135	0	0.084375	0.100224	0.09354	0.1395	0.06417	0.153667
CNTL53	0.07688	0.09	0	0.045	0.076989	0.090675	0.13473	0.071856	0.0531	0.080528	-0.12967
CNTL54	0.105192	0.132632	0.54	0.18	0	0.09585	0.15755	0.118164	0.0963	0.092408	0.085667
CNTL55	0.069054	0.052105	0	0	0	0.106875	0.104999	0.12	0.1611	0.2025	0.259167
CNTL56	0.084246	0.066316	0.18	0.045	0.070251	0.07785	0.110655	0.065574	0.081	0.109283	0.051167
CNTL57	0.144092	0.123158	0	0.09	0	0.09	0.079074	0.03834	0.1233	0.084803	0.311833
CNTL58	0.080102	0.071053	0	0.135	0	0.092363	0.116379	0.034482	0.0936	0.055508	0.141
CNTL59	0.170563	0.118421	0.36	0.225	0.17352	0.07965	0.097164	0.072876	0.07245	0.1134	-0.216
CNTL60	0.105422	0.108947	0.18	0.045	0.112294	0.074138	0.068778	0.117906	0.108	0.163373	0.134667
CNTL61	0.054092	0.056842	0.18	0.18	0	0.086963	0.114894	0.127662	0.05535	0.093758	0.137167
CNTL62	0.078721	0.132632	0	0.045	0	0.104175	0.092106	0.070176	0.13005	0.053033	-0.044
CNTL63	0.122455	0.094737	0.18	0.045	0.09666	0.094725	0.118422	0.090228	0.12555	0.145125	0.144167
CNTL64	0.046957	0.052105	0	0	0	0.09	0.22059	0.117648	0.13635	0.079763	0.391333
CNTL65	0.071816	0.094737	0	0	0	0.094725	0.115385	0.096156	0.11655	0.09	0.0965

Appendix B: Scoring Tables

Table B-1

*Scoring for WEISS Record Questionnaire**

Opposition Defiance Disorder (ODD) - (requires > 4 "Pretty Much" or "Very Much" to be considered for ADHD)	
Question number	*Question*
OQ1	Loses temper
OQ2	Argues with adults
OQ3	Actively defies or refuses to comply with requests or rules
OQ4	Deliberately annoys people
OQ5	Blames others for his or her mistakes or misbehaviour
OQ6	Touchy or easily annoyed by others
OQ7	Angry or resentful
OQ8	Spiteful or vindictive
Anxiety (requires "Pretty Much" or "Very Much" for AQ4, AQ7, AQ11, and AQ13 to be considered for ADHD)	
Question number	*Question*
AQ1	Worries about health, loved ones, catastrophe
AQ2	Unable to relax; nervous
AQ3	Chronic unexplained aches and pains
AQ4	Repetitive thoughts that make no sense
AQ5	Repetitive rituals
AQ6	Sudden panic attacks with intense anxiety
AQ7	Excessively shy
AQ8	Refusal to do things in front of others
AQ9	Refusal to go to school, work or separate from others
AQ10	Unreasonable fears that interfere with activities
AQ11	Pulls out hair, eyebrows
AQ12	Nail biting, picking

AQ13	Refusal to talk in public, but talks at home
Depression (requires > 5 "Pretty Much" or "Very Much" to be considered for ADHD)	
Question number	***Question***
D1	Has been feeling sad, unhappy or depressed
D2	No interest or pleasure in life
D3	Feels worthless
D4	Has decreased energy and less productive
D5	Hopeless and pessimistic about the future
D6	Excessive feelings of guilt or self-blame
D7	Self-injurious or suicidal thoughts
D8	Social withdrawal
D9	Weight loss or weight gain
D10	Change in sleep patterns
D11	Agitated or sluggish, slowed down
D12	Decreased concentration or indecisiveness
D13	Past suicide attempts
Mania (requires > 3 "Pretty Much" or "Very Much" to be considered for ADHD)	
Question number	*Question*
MQ1	Distinct period of consistent elevated or irritable mood
MQ2	Grandiose, sudden increase in self esteem
MQ3	Decreased need for sleep
MQ4	Racing thoughts
MQ5	Too talkative and speech seems pressured
MQ6	Sudden increase in goal directed activity, agitated
MQ7	High risk activities (spending money, promiscuity)
Social Skills (requires > 5 "Pretty Much" or "Very Much" to be considered for ADHD)	
Question number	*Question*
SQ1	Makes poor eye contact or unusual body language

SQ2	Failure to make peer relationships
SQ3	Lack of spontaneous sharing of enjoyment
SQ4	Lacks reciprocity or sensitivity to emotional needs of others
SQ5	Language delay or lack of language communication
SQ6	Difficulty communicating, conversing with others
SQ7	Speaks in an odd, idiosyncratic or monotonous speech
SQ8	Lack of creative, imaginative play or social imitation
SQ9	Intensely fixated on one particular interest
SQ10	Rigid sticking to nonfunctional routines or rituals
SQ11	Preoccupied with objects and parts of objects
SQ12	Repetitive motor mannerisms (hand flapping, spinning)
Psychosis (requires > 5 "Pretty Much" or "Very Much" to be considered for ADHD)	
Question number	*Question*
PQ1	Has disorganized, illogical thoughts
PQ2	Hears voices or sees things
PQ3	Conviction that others are against or will hurt them
PQ4	People can read their thoughts, or vice versa
PQ5	Belief that the television is talking specifically to them
PQ6	A fixed belief that is out of touch with reality
PQ7	Thought sequence does not make sense
Learning Disorders (requires "Pretty Much" or "Very Much" for LQ3, LQ4, LQ5, LQ8 considered for ADHD)	
Question number	*Question*
LQ1	Delayed expressive language
LQ2	Stuttering
LQ3	Problems articulating words
LQ4	Below grade level in reading
LQ5	Below grade level in math
LQ6	Trouble with writing (messy, tiring, avoids writing)

LQ7	Variable performance in school
LQ8	Underachieves at school relative to potential
Personality Disorder (requires > 5 "Pretty Much" or "Very Much" to be considered for ADHD, excluding PDQ5, PDQ10, and PDQ11)	
Question number	*Question*
PDQ1	Unstable interpersonal relationships
PDQ2	Frantic efforts to avoid abandonment
PDQ3	Recurrent suicidal ideation or attempts
PDQ4	Intense anger
PDQ5	Major mood swings
PDQ6	Impulsive self-destructive or self-injurious behavior
PDQ7	Fragile identity or self-image
PDQ8	Chronic feelings of emptiness
PDQ9	Transient stress related dissociation or paranoia
PDQ10	Self centred or entitled
PDQ11	Deceitful, aggressive, or lack of remorse

*** Notes:**

- Number values for scoring as follows:
- Not measuring "Conduct Disorder" as that measures violent and manipulative traits that are not linked in ADHD symptoms
- Not measuring "Tic Disorder" as that is already asked on the "Tourette's" question of the physical questionnaire
- Not measuring "Substance Abuse" as that is already asked on the "Substance Abuse Injuries" question of the physical questionnaire
- Not measuring "Sleep Disorders" as that is already asked on the "Sleep Disorders" question of the physical questionnaire

- Not measuring "Elimination Disorders" (traits not related to ADHD symptoms)
- Not measuring "Eating Disorders" (traits not related to ADHD symptoms)
- Not measuring "Developmental Coordination Disorder" as that is already asked on the "Coordination Problems" question of the physical questionnaire

Table B-2

Scoring for ASRS Questionnaire (World Health Organization, 2015)

Part A (more than 4 for "Often" or "Very Often" indicates prevalence of ADHD)	
Question number	*Question*
Q1	How often do you have trouble wrapping up the final details of a project, once the challenging parts have been done?
Q2	How often do you have difficulty getting things in order when you have to do a task that requires organization?
Q3	How often do you have problems remembering appointments or obligations?
Q4	When you have a task that requires a lot of thought, how often do you avoid or delay getting started
Q5	How often do you fidget or squirm with your hands or feet when you have to sit down for a long time?
Q6	How often do you feel overly active and compelled to do things, like you were driven by a motor
Part B (probing questions - optional)	
Question number	*Question*
Q7	How often do you make careless mistakes when you have to work on a boring or difficult project?
Q8	How often do you have difficulty keeping your attention when you are doing boring or repetitive work?
Q9	How often do you have difficulty concentrating on what people say to you, even when they are speaking to you directly?
Q10	How often do you misplace or have difficulty finding things at home or at work?
Q11	How often are you distracted by activity or noise around you?

Q12	How often do you leave your seat in meetings or in other situations in which you are expected to stay seated?
Q13	How often do you feel restless or fidgety?
Q14	How often do you have difficulty unwinding and relaxing when you have time to yourself?
Q15	How often do you find yourself talking too much when you are in social situations?
Q16	When you're in a conversation, how often do you find yourself finishing the sentences of the people you are talking to, before they can finish it themselves?
Q17	How often do you have difficulty waiting your turn in situations when turn taking is required?
Q18	How often do you interrupt others when they are busy?

Appendix C: Research of Ethics Board Approval

Athabasca University
RESEARCH CENTRE

CERTIFICATION OF ETHICAL APPROVAL

The Athabasca University Research Ethics Board (AUREB) has reviewed and approved the research project noted below. The AUREB is constituted and operates in accordance with the current version of the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS) and Athabasca University Policy and Procedures.

Ethics File No.: **22808**

Principal Investigator:
Ms. Diane Mitchnick, Graduate Student
Faculty of Science & Technology\Master of Science in Information Systems

Supervisor
Dr. Vivekanandan (Vive) Kumar (Supervisor)
Dr. Shawn Fraser (Invited Partner/Partner Organization)

Project Title:
Using Healthcare Analytics to Determine ADHD in students

Effective Date: December 23, 2017 **Expiry Date**: December 22, 2018

Restrictions:

Any modification or amendment to the approved research must be submitted to the AUREB for approval.

Ethical approval is valid *for a period of one year*. An annual request for renewal must be submitted and approved by the above expiry date if a project is ongoing beyond one year.

A Project Completion (Final) Report must be submitted when the research is complete *(i.e. all participant contact and data collection is concluded, no follow-up with participants is anticipated and findings have been made available/provided to participants (if applicable))* or the research is terminated.

Approved by: **Date:** December 23, 2017

Ali Akber-Dewan, Chair
School of Computing & Information Systems, Departmental Ethics Review Committee

Athabasca University Research Ethics Board
University Research Services, Research Centre
1 University Drive, Athabasca AB Canada T9S 3A3
E-mail rebsec@athabascau.ca
Telephone: 780.675.6718

Figure C-1. Certification of approval for the MHADS Study.

Appendix D: Registration and Consent Form

Home Page Info:

MHADS Experiment

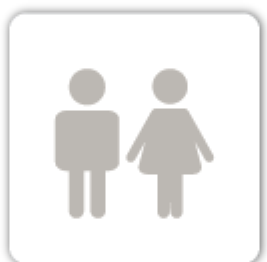
for more study information

A cash incentive of $60 will be e-transferred to participants

after completion of the study.

Part 1

ONLY 1 HOUR OF YOUR TIME!



Demographic Questionnaire

Physical

Questionnaire

Behavioral

Rating Scales

Reaction-based

Continuous

Performance Test

Part 2

ONLY 2 HOURS OF YOUR TIME!

Writing

Study Info:

For your participation, time, and effort, you will receive a compensation of $60!

Study Information

A study on the impact of mental health in learning

Ms. Diane Mitchnick (Lead researcher, graduate student)

School of Computing and Information Systems

Athabasca University

Third party (To be contacted for any questions or concerns)

thirdparty@athabascau.ca

You are invited to participate in a research study validating screening tools to assess one's mental health. This study involves two steps within a week of each other. This study officially starts on (4/30/18).

As a participant of the study, you will be asked to 1) fill out four questionnaires, complete a performance test and to 2) write a 300-word paragraph in English on a specific subject.

Participation to complete both parts of this study (questionnaires, performance test and writing task) will take approximately 3 hours of your time.

For your participation, time, and effort, 1) you will receive a compensation of $60 once you will have submitted all four questionnaires; performance test and submitted your 300-word paragraph.

You may withdraw from the study at any time for any reason during the data collection period by emailing the third party or by clicking on the “Withdraw” button within the Moodle environment. Once withdrawn, your data will be removed immediately from the data storage computers of the study. Your decision about not to continue participating will not influence your relationship or the nature of your relationship with researchers or with staff of Athabasca University either now or in the future. However, if you decide to stop participating, you will no longer be eligible to receive the promised financial benefit.

The risks to participate in this study are minimal. Involvement in this study is entirely voluntary and you may refuse to answer any questions or to share information that you are not comfortable sharing.

The results of this study will be published in journal articles and/or conference papers. Personal information will be published only in a summarized fashion that will not lead to the identification of individual participants. You can request a copy of summary of the results by emailing the third party. If you have any questions about this study or require further information, please contact the third party using the contact information above.

This study has been reviewed by the Athabasca University Research Ethics Board. Should you have any comments or concerns regarding your treatment as a participant in this study, please contact the third party or the Office of Research Ethics at 1-800-788-9041, ext. 6718 or by e-mail to rebsec@athabascau.ca.

If you are interested to participate, click on Register below.

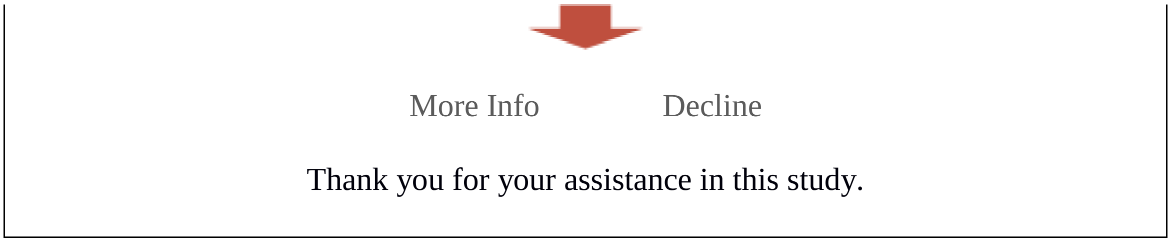


Figure D-1. Study information.

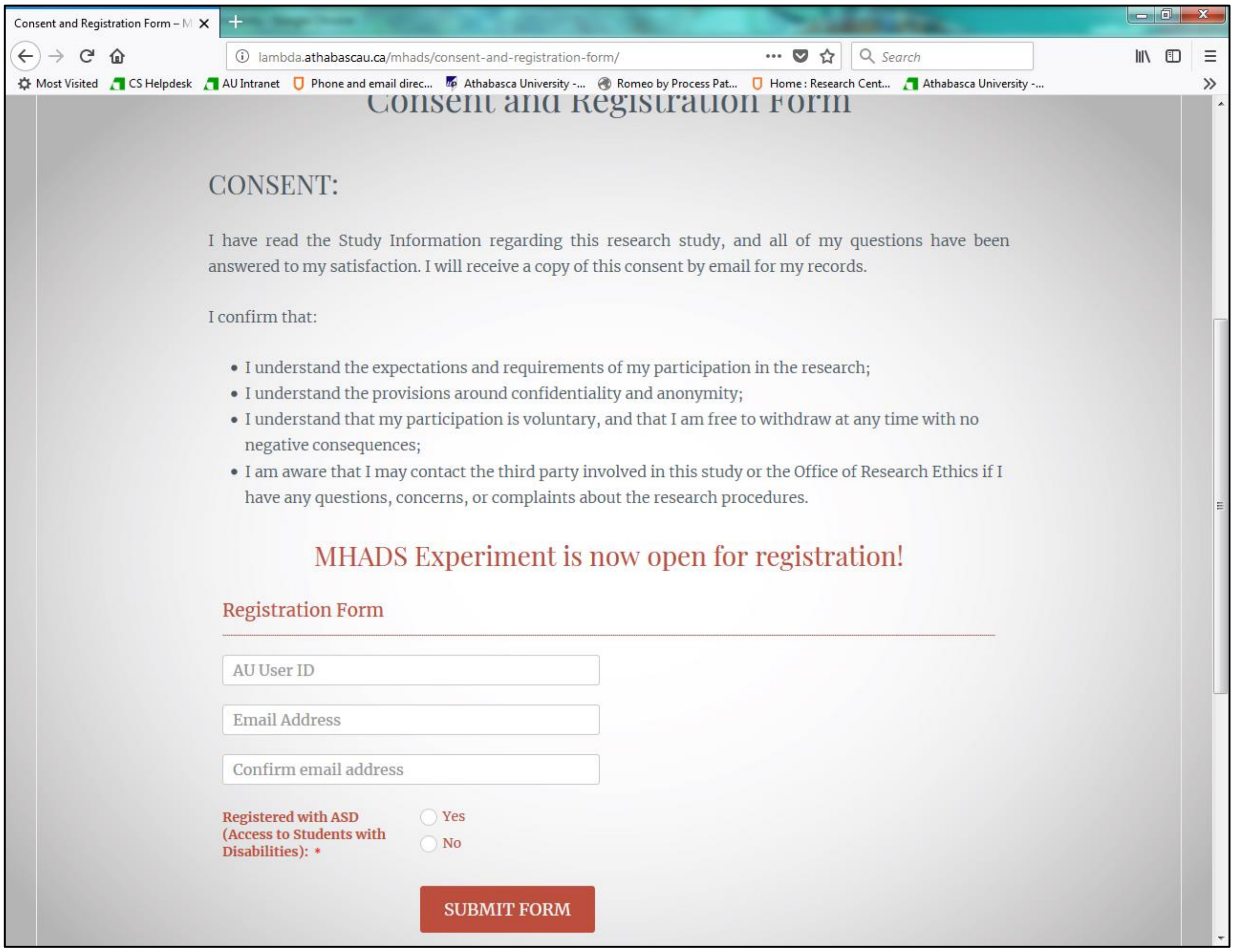


Figure D-2. Registration and Consent Form.