

Measuring the Written Language Disorder among Students with Attention Deficit Hyperactivity Disorder

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Structured Abstract

- **Background:** Attention Deficit Hyperactivity Disorder (ADHD) is a mental health disorder. People diagnosed with ADHD are often inattentive (have difficulty focusing on a task for a considerable period), overly impulsive (make rash decisions), and are hyperactive (move excessively, often at inappropriate times). ADHD is often diagnosed through psychiatric assessments with additional input from physical/neurological evaluations.

Written Language Disorder (WLD) is a learning disorder. People diagnosed with WLD often make multiple spelling, grammar, and punctuation mistakes, have sentences that lack cohesion and topic flow, and have trouble completing written assignments. Typically, WLD is also diagnosed through psychological educational assessments with additional input from physical/neurological evaluations.

- **Literature Review:** Previous research has shown a link between ADHD and writing difficulties. Students with ADHD have an increased likelihood of having writing difficulties, and rarely is there a presence of writing difficulties without ADHD or another mental health disorder. However, the presence of writing difficulties does not necessarily indicate the presence of a WLD. There are other physical and behavioral factors of ADHD that can contribute to a student having a WLD as well. Therefore, a statistical association between these factors (in conjunction with written performance) and WLD must first be established.
- **Research Question:** To determine the statistical association between WLD and physical and behavioral aspects of ADHD that indicate writing difficulties, this research reviewed methodologies from the literature pertaining to contemporary diagnoses of writing difficulties in ADHD students, and reveal diagnostic methods that explicitly associate the presence of WLD with these writing difficulties among students with ADHD. The results demonstrate the association between writing difficulties and WLD as it pertains to ADHD students using an integrated computational model employed on data from a systematic review. These results will be validated in a future study that will employ the integrated computational model to measure WLD among students with ADHD.
- **Methodology:** To measure the association of WLD among students with ADHD, the authors created a novel computational model that integrates the outcomes of common screening methods for WLD (physical questionnaire, behavioral questionnaire, and written performance tasks) with common screening methods for ADHD (physical questionnaire, behavioral questionnaire, adult self-reporting scales, and reaction-based continuous performance tasks (CPTs)). The outcomes of these screening methods were fed into an artificial neural network (ANN¹) first, to ‘artificially learn’ about measuring the prevalence of WLD among ADHD students and second, to adjust the prevalence value based on information from different screening methods. This can be considered as the priming of the ANN. The ANN model was then tested with data from previous studies about ADHD students who had writing difficulties. The ANN model was also tested with data from students without ADHD or WLD, to serve as control.

¹ ANN is a computational model that attempts to mimic the functioning of a human brain.

- **Results:** The results show that physical, behavioral, and written performance attributes of ADHD students have a high correlation with WLD ($r = 0.72$ to 0.80) in comparison to control students ($r = 0.30$ to 0.20), substantiating the link between WLD and ADHD. It should be noted that due to lack of female participation, most studies in the literature only employed and reported on the relationship between WLD and ADHD for male participants.
- **Discussion and Conclusion:** By testing ADHD students and control students against the WLD criteria, the study shows a strong correlation between WLD and ADHD. There are limitations to the results' accuracy in terms of a) sample size (average $n=88$, mean age = 19, 8 studies used for a meta-analysis), b) analysis (original study reviewing ADHD factors first, WLD factors second), and c) causation (the study only reviews prevalence of WLD in ADHD students, not causation). A clinical trial will validate the data and address some of these limitations in a future phase of the research. A computational causal model will be introduced in the discussion portion to illustrate how causation between writing metrics and WLD as it pertains to ADHD can be achieved. These results open the door to advancing pedagogical techniques in education, where students afflicted with ADHD and/or WLD could not only receive assistance for the behavioral aspects of their disorder, but also expect assistance for the learning aspects of their disorder, empowering them to succeed in their studies.

Keywords: ADHD, attention deficit hyperactivity disorder, data analytics, neural networks, WLD, written language disorder

1.0 Background

Attention Deficit Hyperactivity Disorder (ADHD) affects 1 in 10 school-age children in the United States (Bitsko, Danielson, Holbrook, Visser, & Zablotsky, 2015). This disorder is diagnosed primarily when a child is 7 years of age, and even with treatment the disorder continues to be present in the child's adult life, affecting social and learning behavior, including post-secondary years.

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 Diagnostic and Statistical Manual of Mental Disorders, or DSM 5) occurring in students as well (Barbarese,

Colligan, Katusic, & Weaver, 2009). This disorder is commonly associated with other mental health disorders such as ADHD or autism, but it can occur as a learning disability without a mental health disorder. WLD is also usually diagnosed when a child is 7 years of age, and the symptoms follow well into adulthood.

Previous research indicates a link between ADHD and writing difficulties. ADHD students have been shown to have a weakness of working (short-term) memory. Therefore, their composition skills are not learned at the moment they are taught (Yoshimasu, et al., 2011). In a study at the Universidad de Valencia in Spain, students with ADHD were found to lack attention to detail required for writing letters legibly by hand (Casas, Ferrer, & Fortea, 2013). In another study at the University of Padova, Italy, ADHD students were found to be impulsive in their writing structure, writing quickly to get their ideas on paper and sacrificing legibility and composition in future reviews of their notes (Re & Cornoldi, 2010).

However, as the studies indicate, measuring the link between writing difficulties and WLD in ADHD students is not easy. Mental health disorders and learning disabilities are not readily diagnosable, as they revolve around behavioral learning performance symptoms that are less deterministic, instead of physical symptoms that are more factual. This research posits that a computer-based evaluation of the written performance of ADHD students could benefit from data sets that incorporate the student's physical, behavioral, and learning performance, data sets that are interoperable, and algorithms that are aware of each other's outcomes.

To determine the statistical association between writing difficulties and WLD in ADHD students, this research will review the methodology from the literature pertaining to contemporary measures of writing difficulties in ADHD students, and reveal techniques that explicitly associate the writing difficulties with the WLD for the ADHD student. The results will be validated in a study that employs an integrated computational model on student data to address the aforementioned goal.

2.0 Literature Review

Writing is a discipline that has pervaded everyday life and education for centuries. This section offers a review of writing difficulties among students diagnosed with ADHD.

2.1 Methods for Measuring Writing Difficulties in ADHD Students

A literature review was completed to identify common methods that are currently used for screening ADHD (Mitchnick, Kumar, Kinshuk, & Fraser, 2016). This review explicates a set of writing-related factors that were linked to WLD.

A study at the University of Valencia investigated the presence of written expression difficulties among students who were already diagnosed with ADHD (Casas, Ferrer, & Fortea, 2013). The participants of the study were administered neurological/physical assessments and Conner's rating scale ($T > 65$ screens). The study used variables that traditionally have been used in rating narrative discourse, and more specifically, measures/variables that had been used in the expression, reception and recall of narrative instrument (ERRNI) (Bishop, 2004). The measures were broken down by 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 measures were also broken down by a 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 measures also considered revisions that include 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. Instead, the focus of the study was about highlighting written difficulties in general.

A study at the University of Pedova explored the prevalence of spelling errors among the written compositions of students diagnosed with ADHD (Re, Mirandola, Esposito, & Capodieci, 2014). The study concluded that spelling was linked to the phonological working memory of the student. In this study, two sets of written tasks were administered to 19 ADHD students and 19 “normal” students. All the students were 10-year-old males. The ADHD students were screened using teacher interviews and the Italian equivalent of ASRS² (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 non-phonological) 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 demonstrated that the phonological working memory of the ADHD students was lower than that of the normal group, and that the ADHD group was more prone to spelling, sequence, and morphosyntactic errors.

Re, Mirandola, Esposito, and Capodieci (2014) recognize that they are focusing on a very specific part of written expression and acknowledge that they would benefit from a third task that would collect performance data not related to working memory. 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 study at the University of Nebraska targeted the writing difficulties of ADHD students (Jacobson & Reid, 2012). Student writing difficulties were measured using rating scales and parent interviews, followed by a Test of Written Language (TOWL-3). Writing difficulties were measured in terms of 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 on these measures, teachers could use a

² ADHD Self Reporting Scale; a scale used for diagnosing ADHD (World Health Organization, 2015).

Self-Regulated Strategy Development (SRSD) model to guide ADHD students in their writing. The application of the SRSD model showed that ADHD students vastly improved in many writing difficulty areas.

While the study had a small sample size of four student participants, combining the writing performance test with the rating scales and the behavioral interviews highlighted the need to integrate multiple datasets from different screening tools in WLD and ADHD-related research. This study did not identify attributes for measuring WLD, but it did identify attributes for measuring writing difficulties which can be associated with WLD.

A study conducted at a rural elementary school in a Midwestern state assessed the effectiveness of a validated strategy instruction model—Self - Regulated Strategy Development (SRSD)—on the length, completeness, and quality of written narratives completed by three children who were identified by their teacher as having writing difficulties and diagnosed with ADHD by a physician (Lienemann & Reid, 2006). The measures used in this study include the number of words, the number of story parts (that captured connective cohesion—if the story parts flowed), and quality ratings (that captured cohesive adequacy—if the quality of the story parts were complete). This study also had a much smaller sample size and involved a teacher to identify student participants with writing difficulties, which might have created a bias.

A literature review using Woodcock-Johnson (WJ) tests (WJ III Tests of Achievement, 2001) was conducted to identify students with special needs that had writing difficulties. Along with other behavioral disorders, the review studied the use of WJ tests on the writing composition of ADHD students (Schrank, 2005). The review covered cognitive concepts such as cognitive efficiency, processing speed, short-term memory, and long-term retrievals— traits that are also linked with a “written language” deficiency. A cluster analysis was conducted on spelling, writing fluency, writing content, and editing variables from the writing samples of the ADHD group. The review found that the ADHD group scored low on the abovementioned concepts and scored low on overall written language fluency. The review did not have set writing-related factors that could be used to measure WLD. However, it offers a good start for defining a standard scale for measuring writing performance among ADHD students.

Based on the literature reviewed so far, a comparison table (Table 1) has been created that identifies factors one can use to measure writing performance of students afflicted with ADHD. This list of factors offers a more definitive set of measures that associates WLD with ADHD. Other behavioral disorders that might affect written performance can be ruled out with pre-screens of cognitive concepts mentioned above. Combining the outcomes of different screening tools enables the inclusion of physical or behavioral factors (symptoms).

Table 1

Variables Used for Measuring Writing Difficulties in ADHD¹ Students in a Systematic Review

Writing Variables	Casa, Ferrer, & Fortea (2011)	Capodieci, Esposito, Mirandola, & Re (2014)	Lienemann & Reid (2006)	Schrank (2005)	Jacobson & Reid (2012)
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	
Uncorrected content errors	x			x	
Corrections					
Formal (spelling) revisions	x				
Content (grammatical) revisions	x			x	
Type-token ratio corrected	x			x	
Numbers					
Number of words	x	x	x		x
Number of sentences	x	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

¹ Attention Deficit Hyperactivity Disorder

3.0 Research Question and Hypothesis

To determine the statistical association between WLD and physical and behavioral aspects of ADHD that indicate writing difficulties, this research reviewed methodologies pertaining to contemporary diagnoses of writing difficulties in ADHD students, and reveal diagnostic methods that explicitly associate the presence of WLD with the observed writing difficulties exhibited by students with ADHD. An integrated computational model that employs an Artificial Neural Network (ANN) has been developed, which accepts measures of writing difficulties as input and produces measures of WLD as output. The results demonstrate the association between writing difficulties and WLD as it pertains to ADHD students. This ANN and its outcomes will be validated in a future study that is currently undergoing an ethics review.

The following research question is situated in the context where comprehensive lists of screening methods for writing difficulties are combined in a computational ANN model. The ANN takes the ADHD student's physical, behavioral and writing data as input.

Research Question: What are the factors that can measure the presence of writing difficulties associated with WLD in ADHD students?

The hypothesis states that the combination of written performance tests with other WLD screening methods (physical screens and behavioral rating scales) will offer a more effective association in determining the presence of WLD in ADHD students than using the written performance tests or the screening methods alone. A key contention in support of this hypothesis states that each method is expected to have behavioral and performance factors that can affect each other, thus improving the effectiveness of association by the combination of methods. The factors are first determined through the systematic review and then modeled for testing, using an artificial neural network (explained in the "Results" section) to measure the presence of WLD.

4.0 Research Methodology

4.1 Analysis Plan

Using data from existing studies on writing difficulties in students afflicted with ADHD, the following metrics were calculated: mean sample size, mean age, physical questionnaires results, behavioral questionnaires results, and written performance metrics. These datasets were projected as common screening

measures for writing difficulties in ADHD students. The results of the measures were then correlated against the WLD classifier with an ANCOVA model. The gaps in the information (such as a physical injury that would bias the analysis) were then flagged for consideration during the interpretation of outcomes. The analysis of the screening measures gave insight into the accuracy of the association with WLD attributes through the strength of the correlation coefficient between the attributes and the written difficulty measures. The analysis also examined if the correlation coefficient between the student writing difficulties and the classifier was a positive and linear one, the cut off being in the range of 0.7 to 1. If the strength of the relationship (or the association) was less than 0.7, then the relationship/association was deemed as moderate or weak. A formalized mathematical model based on causal relations of factors that affect the diagnostic process was then created to validate the performance metrics. This causal model will be introduced later in the “Discussion” section.

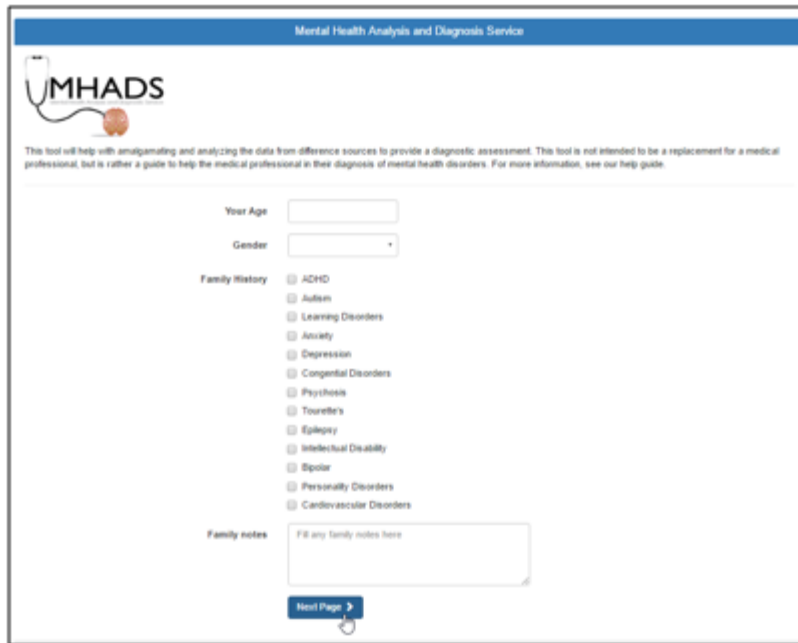
4.2 Methods for Measuring WLD in the ADHD student

The ANN model has been developed as a web application and hence can take online data streams for its input. The ANN, in the upcoming experimental study, will be administered to two student groups: one group being students from a special needs program that have already been diagnosed with ADHD, and another group being the control group, which would comprise of those outside the program that have not been diagnosed with ADHD. A research ethics application is already underway with Athabasca University to obtain consent and invite participation from members of these two student groups.

The ANN model will seek input from the two groups in two stages. First, on day one, the ANN will collect metrics such as age, gender, family history for demographics, physical symptoms (if any), behavioral symptoms that fall outside of WLD symptoms (if any), and behavioral symptoms that are included in the WLD definition. Second, over two days, the ANN will collect data on a written performance test that will focus on written expression and composition.

To exemplify the two stages, the ANN model has been used on data from the systematic review, as indicated in Table 2 of the “Results” section. The screens of the ANN model are outlined below.

The demographics screen (Figure 1) collects students’ age, gender, and family history related to WLD.



Mental Health Analysis and Diagnosis Service

MHADS

This tool will help with amalgamating and analyzing the data from different sources to provide a diagnostic assessment. This tool is not intended to be a replacement for a medical professional, but is rather a guide to help the medical professional in their diagnosis of mental health disorders. For more information, see our help guide.

Your Age

Gender

Family History

- ADHD
- Autism
- Learning Disorders
- Anxiety
- Depression
- Congenital Disorders
- Psychosis
- Tourette's
- Epilepsy
- Intellectual Disability
- Bipolar
- Personality Disorders
- Cardiovascular Disorders

Family notes

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Figure 1. View of demographics questionnaire.

A previous review revealed commonly used screens for ADHD (Mitchnick, Kumar, Kinshuk, & Fraser, 2016). From that review, the following three screens yielded measures that were deemed suitable as inputs for the ANN model in determining the presence of WLD.

A physical questionnaire (Figure 2) was created for this study, based on a screen from the Canadian ADHD Resource Alliance (CADDRA, 2014). This questionnaire filters out physical health issues that would mimic WLD and ADHD symptoms (e.g., head trauma, hearing/visual problems). If the student had any of these issues, they would not qualify as a candidate for the study.

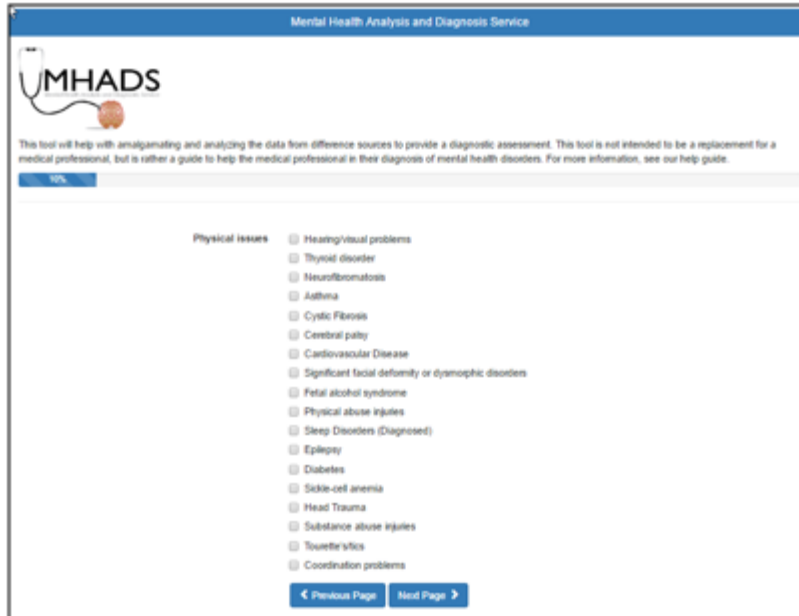


Figure 2. View of screen for physical health issues.

The WEISS Record Scale (Figure 3) has been designed to filter out other learning disorders that have symptoms similar to WLD. For instance, Dyslexia, Auditory Processing Disorder (APD) and other similar mental health disorders (e.g., anxiety, Tourette's) can affect WLD and yet are not related to ADHD (CADDRA, 2014). Each section of the scale has indicators from the DSM-5 for other mental health disorders. In the scale, a score of 0 indicates "Not at all," 1 indicates "Somewhat," 2 indicates "Pretty Much," and 3 indicates "Very Much". The scores are totaled as a sum of responses for a given mental health disorder. For instance, with anxiety, "Pretty Much" or "Very Much" on questions regarding "worrying" or "nervousness" did not indicate the presence of ADHD. The scores also calculated a sum of certain responses for a given learning disorder. For example, "below grade level in reading" and "below grade level in math" did not indicate WLD.

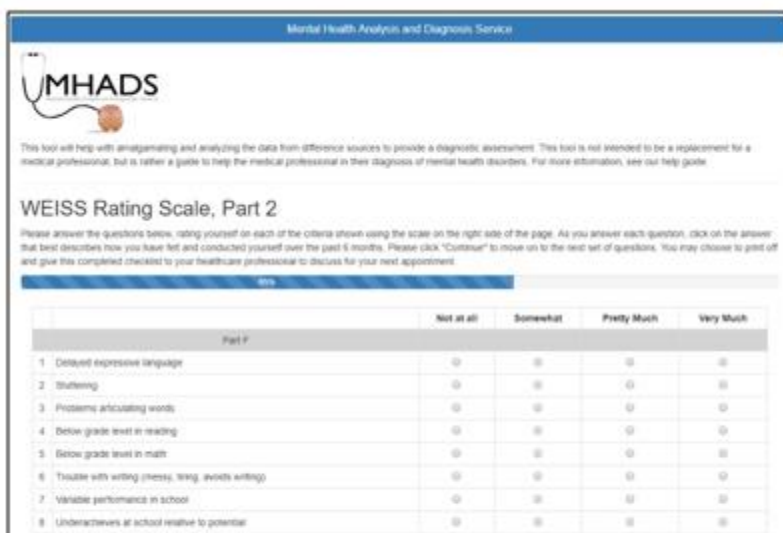


Figure 3. View of screen for mental health and learning issues.

A standard screen for WLD has not been derived yet by the WLD community. To address this gap, a systematic review was completed on the studies of ADHD students with written language and written expression difficulties. Key outcomes of this review are presented in Table 1 and in Table 2. The following metrics were gleaned as part of the proposed standard for measuring WLD in ADHD students:

Errors:

- Spelling errors (norm = 25 errors 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) (Breux & Frey, 2017).

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).

Corrections:

- Number of spelling errors corrected (norm = 90% of misspelled words corrected)
- Number of grammatical errors corrected (norm = 90% of grammar corrected)

If the score for any of the correction metrics is lower than norm, it is an indication of written language composition deficiencies at a writing process level (i.e., measures student's editing skills).

Numbers:

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

If the score for any of the number metrics is lower than norm, it is an indication of written language composition deficiencies at a sentence level (i.e., complexity of sentence structure).

Pairing

- Connective Cohesion (number of sentences paired together based on relationship) – synonyms and connectors for connectivity
- Cohesive Adequacy (number of incomplete sentences) – check for punctuation mark. Check for verb ending a sentence (“was.”)

If more than 5 concepts are missed or unrelated out of 10, it is an indication of written language composition deficiencies on a discourse level (i.e., organization of narratives and cohesion).

Using these metrics, a Writing Analytics CPT screen (Figure 4) can be created that tracks real time measurements of these writing-related metrics (Clemens, 2011, 2017; Kumar, 2015; Boulanger, 2016).

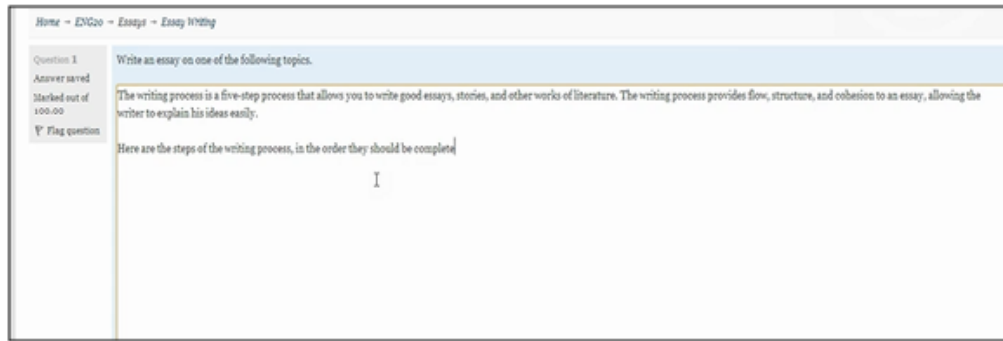


Figure 4. View of screen for Writing Analytics CPT.

4.3 Methodology for Analysis

The integrated ANN model collects data from screens separately and then feeds the data through a neural network to weigh its importance to the DSM classifier. As an example, consider that a DSM classifier was made up of 5 attributes for spelling and 5 attributes for written language composition. These 10 attributes are expected to be present in order in order to meet the WLD definition. Figure 5 illustrates this example DSM classifier as a neural network. The rules that would have to be met to confirm WLD diagnosis. The dark blue data input nodes would each have the black metrics (scales) in a hidden layer (hidden layer nodes), with initial weights attached to them in relation to the output node (the classifier). While the metrics themselves could not change, the weight they are given (adjacent to the light blue weight indicators) would change. These weights are known as synaptic or connection weights. In this example, even though there is no connection for WLD in the WEISS input initially (that is, the strength of the connection from the WEISS node to the hidden layer “Point Scale” node is 0, 0), it is still considered as a connection to the classifier (albeit a weak one), since the weight is adjusted after other input nodes are reviewed for their connection to the output node. If another input node (“Physical” for example) has a strong connection to the output node, that connection weight is used toward the overall connection (or relationship strength) for the WLD DSM classifier.

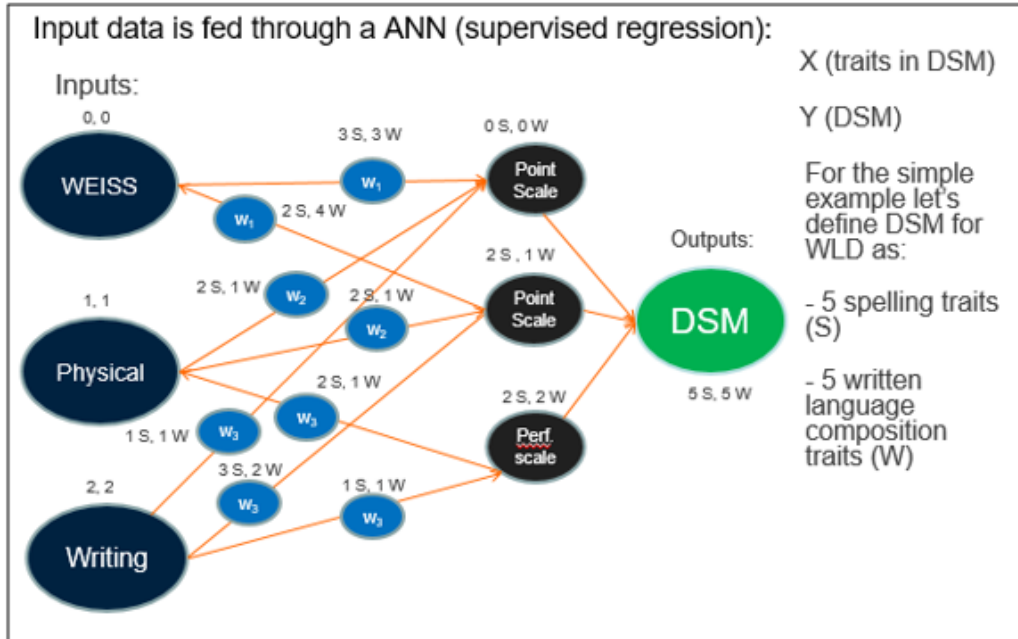


Figure 5. Example of using screening method inputs, with hidden layer metrics (scales) to get the desired output (WLD DSM classifier).

The formula to calculate the synaptic weight strength is shown in Figure 6, where y_j is the estimated output node where y_j is the estimated output node, and w is the weight of the input node, and x is the input node. So in this example, the $w_1x_1 + w_2x_2$ is $(3,3)*(0,0) + (2,1)*(1,1) = (2,1)$. This estimated output is nowhere near the output that is required $(5, 5)$, but the weights for the WEISS and Physical nodes can now be changed to $(2, 1)$ and the algorithmic formula is retrained to use the next group of data with these new weights on the nodes.

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

Figure 6. Calculation for synaptic weight (w) with the initial input node (x) to determine the estimate output node (y).

5.0 Results

With input from the outcomes of a few more studies, Table 2 produces data that can be used to train the neural network model.

Table 2

Demographics and Correlation Values Matched against the WLD¹ DSM² Classifier for ADHD⁶ Groups

Study	Demographics			Input Measures Weighted			Total
	Mean Age	Gender	Family History	Physical ³	WEISS ⁴	Written CPT ⁵	DSM Output ₂
Casa, Ferrer, & Fortea (2011)	12	M	Dyslexia	0	0.3	0.85	0.75
Capodiecì, Esposito, Mirandola, & Re (2014)	20	M	Depression	0	0.2	0.75	0.75
Lienemann & Reid (2006)	9	M	Bipolar	0	0.2	0.8	0.80
Schrank (2005)	30	F	Heart Disease	0	0.1	0.62	0.65
Jacobson & Reid (2012)	9	M	None	0	0	0.78	0.72
Rodríguez, Grünke, González-Castro (2015)	22	M	Tourette's	0	0.1	0.8	0.75
Miranda, Baixauli, Colomer (2013)	21	M	ODD, Anxiety	0	0.2	0.75	0.75
Molitor, Langberg, Evans (2016)	22	F	ODD	0	0.4	0.72	0.73

¹ Written Language Disorder

² Diagnostic and Statistical Manual of Mental Health Disorders

³ Physical Questionnaire (CADDRA, 2014)

⁴ WEISS Records: behavioral questionnaire (CADDRA, 2014)

⁵ Continuous Performance Test

⁶ Attention Deficity Hyperactivity Disorder

For training the model to evaluate student data's association to WLD, the student data (input) must be run through a multilayer perceptron for learning the algorithm that would yield the strongest connection from the student data nodes (nodes from the physical questionnaire, behavioral questionnaire, and written performance measures) to the outcome node (the WLD classifier). By doing so, "backpropagation" can be activated. Meaning, the amount of error can be calculated based on the strength of the connection between the input data node and the output classifier note. The amount of error gives an indication of how close the input node's relationship is to the output note. The strength 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 and studying of the output to get to a significant level of changes to the weights.

To obtain the association for WLD classification and to validate it, the data in Table 2 was run in a multilayer perceptron neural network through IBM's SPSS Statistics 24. Studies are considered valid with respect to the training model if the amount of error in the connection weights of the study data are in relation to the other studies' data (not outside the linear relationship). Seven studies were considered valid (see Figure 7), and one was excluded since the connection (or relationship strength) weights of the other studies were not consistent with the connection weights of the excluded study.

The perceptron also produces a network diagram (see Figure 8). 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.

Case Processing Summary

		N	Percent
Sample	Training	5	71.4%
	Testing	2	28.6%
Valid		7	100.0%
Excluded		1	
Total		8	

Network Information

Input Layer	Factors	1	WEISS
		2	WrittenCPT
	Number of Units ^a		8
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1 ^a		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	WLD
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Figure 7. Analysis of the input factors for training and testing the WLD output in IBM SPSS.

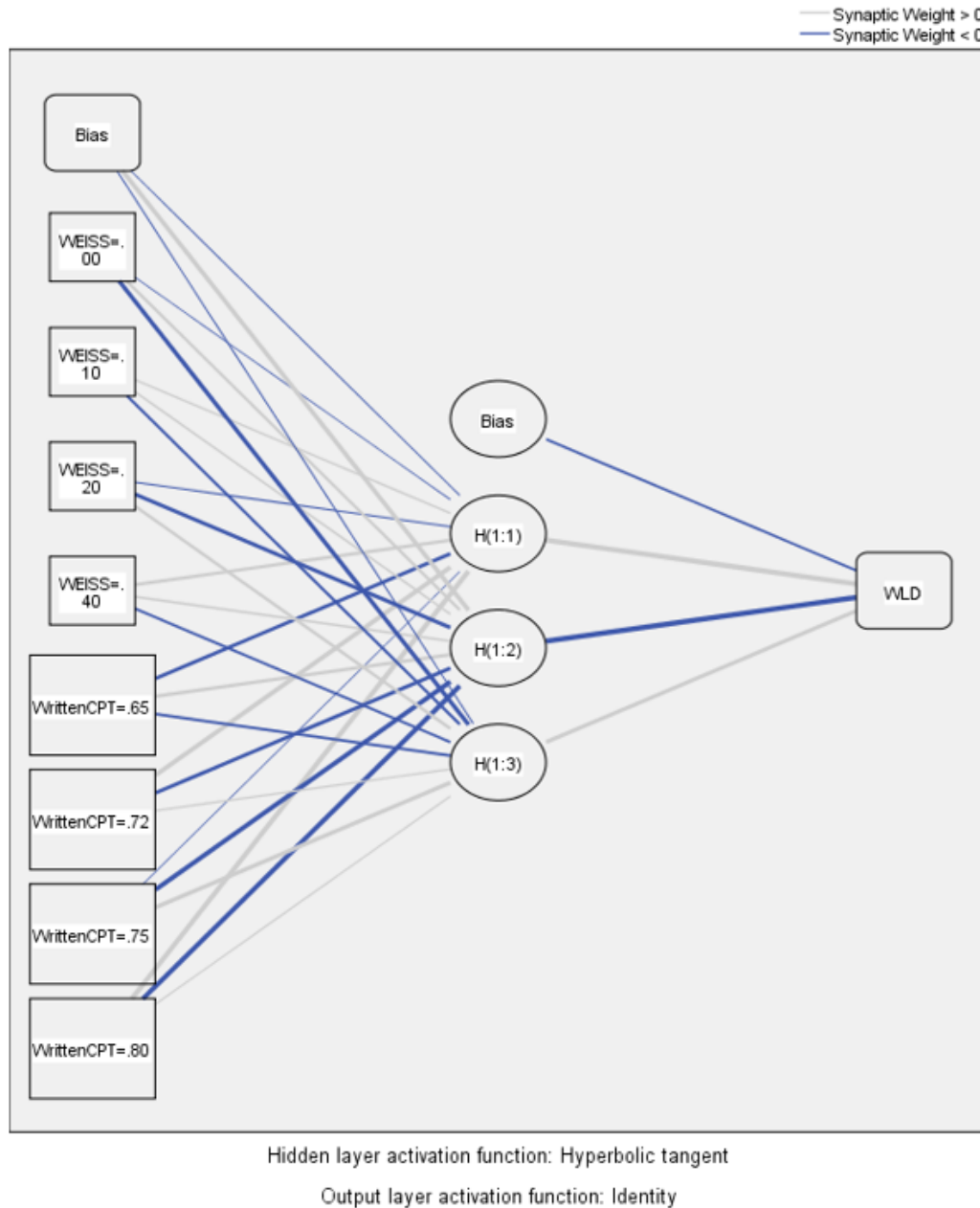


Figure 8. First pass of correlated data for training in SPSS for the WLD DSM output.

As shown in Table 2, there are many correlation values for each dataset. This means that the model has to be refined first to have a more standard training correlation. However, the strong blue line in Figure 8 already shows that there is a link of written performance difficulties to WLD.

The network diagram shows an interesting connection. While the WEISS dataset does not strongly show up as a factor to be considered for measuring the presence of WLD (a correlation of 0.12 r overall), it is the written performance that presents a strong connection (a correlation of 0.74 r overall). Therefore, written performance data of ADHD students can be used to help determine the presence of WLD in ADHD students. As a comparison, the results for the control groups (i.e., students without writing difficulties or ADHD) of these studies are also shown in Table 3.

Table 3

Demographics and Correlation Values Matched Against the WLD¹ DSM² Classifier for Normal Groups

Study	Demographics			Input Measures Weighted			Total DSM Output ²
	Mean Age	Gender	Family History	Physical ³	WEISS ⁴	Written CPT ⁵	
Casa, Ferrer, & Fortea (2011)	12	M	None	0	0.3	0.2	0.2
Capodieci, Esposito, Mirandola, & Re (2014)	20	M	None	0	0.2	0.3	0.3
Lienemann & Reid (2006)	9	M	None	1	0.2	0.2	0.2
Schrank (2005)	30	F	Heart Disease	1	0.1	0.4	0.4
Jacobson & Reid (2012)	9	M	None	0	0	0.3	0.25
Rodríguez, Grünke, González-Castro (2015)	22	M	Tourette's	0	0.1	0.2	0.15
Miranda, Baixauli, Colomer (2013)	21	M	ODD, Anxiety	0	0.2	0.2	0.2
Molitor, Langberg, Evans (2016)	22	F	ODD	0	0.4	0.25	0.2

¹ Written Language Disorder

² Diagnostic and Statistical Manual of Mental Health Disorders

³ Physical Questionnaire (CADDRA, 2014)

⁴ WEISS Records: behavioral questionnaire (CADDRA, 2014)

⁵ Continuous Performance Test

Since there were very few to no connections to the DSM classifier for WLD or ADHD, the results were not run through the training model, as the training data would not be sufficient to indicate the presence of WLD in ADHD students.

6.0 Discussion and Conclusion

While the study showed a presence of WLD in ADHD students, there are limitations to its accuracy.

First, the sample size used for the systematic review was small (average $n=88$, mean age = 19, over 8 studies). This is due to a limited amount of studies that analyze writing difficulties with ADHD students. In fact, only the study by Schrank (2005) touched on the concept of using written composition data to associate writing difficulties with WLD, but this was mentioned as a general concept, since the focus was more on the association with ADHD.

Second, the study described in this article involved physical, behavioral, and written performance as a way to measure WLD for ADHD students. It did not look into other disorders that can affect writing, such as reading disorders or dyslexia. However, more consideration can be included in the screens for these additional disorders. Future research that explores co-morbidity of WLD with other disorders can determine an association with writing difficulties and those disorders then. For now, having a physical questionnaire and behavioral questionnaire as part of the model that can flag these disorders and exclude them from the research to narrow the focus on written language disorder is more effective at determining the association of writing difficulties in ADHD students and WLD, which, by proxy, can determine the presence of WLD in ADHD students more easily.

Lastly, this study indicates an association of WLD for ADHD students with writing difficulties and a presence of WLD in the ADHD student, but not a causation. This implies that it is still uncertain if WLD occurs because of ADHD or if it would happen to the student without ADHD. This study is looking at ADHD students with a presence of WLD, because the literature indicates a link between students with writing difficulties and ADHD. However, it should be noted that this study does not indicate students that have been diagnosed with WLD also have a presence of ADHD. Again, a specific study for the WLD causal model would have to be developed to address these additional scenarios. That said, a causal model has been introduced using writing related measures (Clemens, 2017; Kumar, Clemens, & Harris, 2014), and aspects of that model can be used to create a casual model for WLD.

6.1 Causal Modeling for WLD

Because the presence of WLD 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 can be built that links these metrics. As an example,

the following model was created in Tetrad V for writing metrics on normal 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 competencies) (Clemens, 2017). The same method could be applied to ADHD students' writing competencies to create a covariance matrix for WLD. An example of what this covariance matrix would look like is shown in Figure 9.

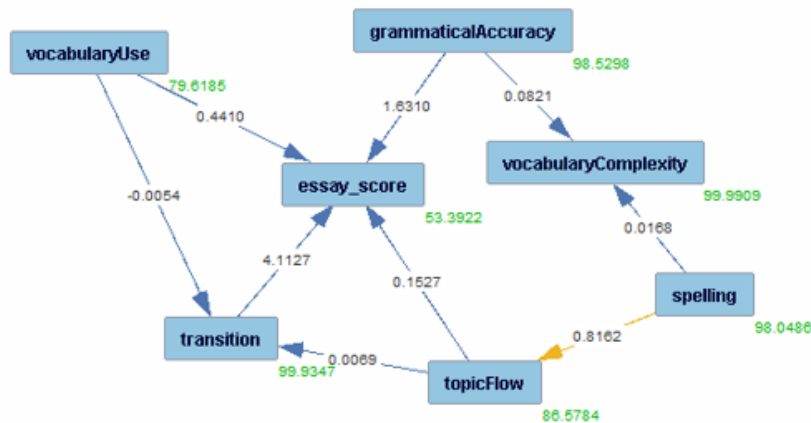


Figure 9. SEM from FGS Search over Competences – Final Essays illustrates observed metrics (blue boxes) that can be used for casual modeling (Kumar, Clemens, & Harris, 2014). The correlations between the metrics to the final score are indicated in the diagram. The z-value (or standard deviation from the metric and final score) is indicated in green.

The spelling errors (**spelling**)—which are indicative of poor spelling, connective cohesion (**topicFlow**)—which is indicative of discourse issues, and grammatical errors corrected (**grammaticalAccuracy**)—which are indicative of sentence difficulties, could contribute to the overall essay score, which could then be applied to a WLD score. These concepts are explained in more detail below.

6.1.1 Spelling. Spelling is potentially exogenous in the system of variables with competences and final essay data. An undirected edge between spelling and topic flow that indicates the causal direction is uncertain in normal 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 of the adjacencies that connect into the spelling competence.

6.1.2 Topic flow. In the competence variable set over final essay 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 normal student writing data. Otherwise, topic flow influences both transition and essay score. Adding the complete event data may reverse many of these relationships. The relation between topic flow and essay score remains consistent in normal 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 of these relationships.

6.1.3 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 of 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 just illustrate what can be done with the model that is already created for normal student writing data.

By testing ADHD students and normal students against the WLD criteria and building a casual model to validate the findings even further, the results open the door to exploring learning methods in education, indicating that not only could ADHD students receive assistance for the behavioral aspects of their disorder, but they could also receive assistance for the learning aspects of their disorder, empowering them to succeed in their studies in the process.

7.0 Directions for Further Research

The initial thesis based on this research detailed the process for gathering the information and the corresponding analysis, including an initial proposed model of adult ADHD with WLD factors.

For this study, student input data from the systematic review was analyzed for the overall correlation between the data (physical, behavioral, and written performance) and the WLD output. This correlation data was the basis for a theoretical model for WLD. However, by running an experimental study in the future, the theoretical results (overall correlation between input data and the output, and strength of that relationship) obtained in this model can be compared against the experimental results. Because the study will compare students that have already been diagnosed with ADHD with those who do not have the disorder (students that have been evaluated to not have a mental health or learning disability), the sample size might be less than what was estimated for an average of the overall studies ($n=88$). The experimental results may differ from the theoretical results as well, since the mean age from the theoretical study is 19 and most of the students in the upcoming study are expected to be significantly older than that. More will be known when the study is complete.

The data collected, and the software used to collect it, in the model could also spark other research into the prevention 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, further analysis could be done on mitigating the influence of those factors and how that mitigation could neutralize WLD.

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, educators can learn about the types of learning styles that can work the best for students with mental health and/or learning disorders.

Author Biographies

Diane Mitchnick holds a Bachelor of Science degree in Computing and Information Systems from Athabasca University, Canada and is currently working on her graduate thesis. Her research areas encompass neural networks and artificial intelligence, with the goal to leverage from these areas a healthcare analytics package that will provide insight into learning the diagnostic behaviour of written language disorder (WLD) in adults with attention deficit hyperactivity

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