Postsecondary Enrolment of Adolescents with and without Childhood ADHD: A Longitudinal Analysis of Academic and Mental Health Trajectories

by

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ABSTRACT

Do adolescents with histories of attention-deficit/hyperactivity disorder (ADHD) who subsequently enrol in post-secondary education differ from their peers with ADHD histories who do not enrol? This thesis explored ADHD histories and post-secondary enrolment as factors that may shape the developmental trajectories of academic outcomes and mental health. Using longitudinal data from the Multimodal Treatment Study of Children with ADHD (MTA) and latent curve modelling, I explored ADHD symptoms, academic outcomes, and anxiety and depression symptoms from ages 9 through 17 for four groups: adolescents with ADHD histories and eventual post-secondary enrolment (n = 332), adolescents with ADHD histories but without post-secondary enrolment (n = 188), adolescents without ADHD histories but with eventual post-secondary enrolment (n = 205), and adolescents with neither ADHD histories nor post-secondary enrolment (n = 45).

From ages 9 through 17, adolescents with ADHD histories who did not eventually enrol in post-secondary studies reported more ADHD symptoms and worse academic outcomes than those who did eventually enrol. Anxiety and depression symptoms were not significantly different across the four groups. Machine learning analyses to classify adolescents with ADHD histories as either "post-secondary" or "no post-secondary" had parallel results, identifying the most important features as academic achievement and ADHD symptoms. In general, academic outcomes were better for adolescents who eventually enrolled in post-secondary studies, regardless of ADHD histories. Among those with ADHD histories, mathematics and English grades declined for those who did not eventually attend post-secondary studies, whereas high school GPA improved for

those who did eventually attend. Thus, to ensure students have an equal opportunity for long-term academic outcomes, it may be particularly important for parents, educators, and clinicians to pay attention to students who have low academic achievement scores, students who have declining grades in middle school, and students with more severe ADHD symptoms. Interventions targeted toward improving academic outcomes, persistent treatment, and coaching strategies may be important ways to support the academic achievements of adolescents with ADHD.

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CHAPTER 1: INTRODUCTION

Children who display a persistent pattern of hyperactivity, impulsivity, and/or inattention that interferes with functioning or development, both at school and at home, may be diagnosed with attention-deficit/hyperactivity disorder (ADHD; American Psychiatric Association, 2013). ADHD is one of the most common neurodevelopmental disorders in childhood (Gupta & Kar, 2010). It is associated with learning difficulties that affect many academic areas, including reading, writing, and mathematics (Dupaul et al., 2013; Frazier et al., 2007). These academic difficulties persist in adolescence, where students with ADHD are eight times more likely to drop out of high school than their typically developing peers (Kent et al., 2011). ADHD was once thought to be a childhood disorder, however, models have been redefined to reflect the disorder's potentially lifelong influence (Rapport et al., 2008). Although only 4-5% of adults meet the diagnostic criteria for ADHD (Kessler et al., 2006), adults with a history of childhood ADHD who no longer meet the diagnostic criteria continue to be functionally impaired in their early twenties (Hechtman et al., 2016; Sibley et al., 2012). Thus, beyond diagnosed cases of ADHD in adulthood, ADHD histories appear to be associated with long-term deficits.

Despite the long-term deficits associated with ADHD, some adolescents with ADHD enrol in post-secondary education. However, in universities and community colleges, 25% of students who seek academic accommodations have ADHD (Green & Rabiner, 2012) and these students are more likely to have lower grade-point averages, graduation rates, and socioeconomic status than other students, and experience more

psychological and emotional difficulties (Barkley et al., 2006; Green & Rabiner, 2012; Mannuzza et al., 1993; Sobanski et al., 2008).

Post-secondary students represent a relatively high-functioning segment of the population (McKee, 2008), but students with ADHD continue to experience academic difficulties in higher education. Beyond admittance to post-secondary programs, do adolescents with ADHD who enrol in post-secondary studies differ from those who do not? The goal of this thesis was to investigate factors that may shape the trajectories of adolescents from four groups: adolescents with ADHD histories who eventually enrolled in post-secondary studies, adolescents with ADHD histories who did not enrol in post-secondary studies, adolescents with no ADHD history who eventually enrolled in post-secondary studies, and adolescents with no ADHD history who did not enrol in post-secondary studies. More specifically, I investigated how symptoms of ADHD and academic outcomes, measured by academic achievement and school performance, changed over time and whether the rates of change differed for adolescents with or without ADHD histories who did or did not enrol in post-secondary studies. Additionally, I investigated how symptoms of anxiety and depression progressed over time and whether the rate of symptom progression differed for adolescents with or without ADHD histories who did or did not eventually enrol in post-secondary studies. These questions were addressed using data from the Multimodal Treatment Study of Children with Attention-Deficit/Hyperactivity Disorder (MTA), a large, longitudinal study that investigated the effectiveness of various types of ADHD treatments. The data were obtained from adolescents with ADHD histories, that is, participants who had a diagnosis of ADHD in childhood, but may not have continued to meet the diagnostic criteria in

adulthood. Additionally, the data were obtained from a local normative comparison group (LNCG) which consisted of adolescents without ADHD histories.

To look for changes in ADHD symptoms, academic outcomes, anxiety, and depression over time, a longitudinal approach is essential. With the increasing availability of longitudinal data comes the increasing need for appropriate statistical analytic methods, that is, analytic methods that allow for greater correspondence between theoretical models and statistical models. There are many statistical techniques available to test longitudinal data (e.g., MANOVA, autoregressive models, difference scores, residualized change scores, latent curve modelling). These models vary in how well they capture the theoretical orientation of the research (Bollen & Curran, 2006).

In this thesis, I used latent curve modelling to establish developmental trajectories. Latent curve modelling is appropriate because information obtained from repeated measurement is used to indirectly observe the trajectory process, allowing for the trajectory to differ by individual case (Bollen & Curran, 2006). Latent growth curves are a tool for estimating the optimal rate and shape of change exhibited by a set of repeated measures. This type of modelling is especially beneficial for studying individual change as a function of time. Thus, I used latent curve modelling to estimate developmental trajectories, with the goal of investigating ADHD histories and post-secondary enrolment as factors that may shape the developmental trajectories of ADHD symptoms, academic outcomes (i.e., academic achievement and school performance), anxiety symptoms, and depression symptoms.

Trajectories of Academic Outcomes

There are multiple ways to measure academic outcomes. For example, academic outcomes can be measured by standardized tests of academic achievement, such as the Wechsler Individual Achievement Test (WIAT), that are designed to measure how an individual is doing in different areas of academic work (Psychological Corp, 1992). Scores reflect performance in core academic subjects, including reading, written language, oral language, and mathematics. Alternatively, academic outcomes can be measured by school grades on report cards or overall grade point average (GPA). However, school grades can reflect a range of situational, cognitive, and affective factors, from child self-control (e.g., Duckworth et al., 2012) to classroom emotional climate (e.g., Reyes, et al., 2012) to student behaviour in the classroom (e.g., Horner et al., 2009). Moreover, although achievement tests and grades are related, the correlation between the two indices is low (Langberg et al., 2011). Hence, students' performance on standardized achievement tests and school grades should be considered as separate outcomes (Raggi & Chronis, 2006). Many children and adolescents with ADHD have both lower standardized academic achievement scores and school grades than their typically developing peers (Barkley et al., 2006; Frazier et al., 2007; Kent et al., 2011), but given that academic achievement tests and school grades are not necessarily tightly linked, I expected adolescents to show different patterns of change in these two indices.

For typically developing students, trajectories of standardized measures of academic achievement increase over time but not at a constant rate. Specifically, these measures increase more slowly for older than for younger students (Chen et al., 2014; Kowaleski-Jones & Duncan, 1999). In contrast, school performance (i.e., report cards,

GPA) increases slightly from Grades 1 through 5, and then decreases slightly from Grades 6 though 12 (Gutman et al., 2003). One possible reason for the differences in trajectories for standardized measures versus grades is that the requirements for standardized testing do not mimic the school environment (Raggi & Chronis, 2006). In school, students must pay attention in class, take good notes, complete assignments, do their homework, and study for tests. These behaviours are monitored closely by parents and teachers in the early school years whereas in later years, more demands are placed on students and they are expected to become more independent. Thus, the increasing demands of the school environment as children progress through their education may be reflected in the changing trajectories.

The increasing demands of school work may be especially challenging for children with ADHD who are known to have difficulties with procrastination, organization, and time management (Langberg et al., 2013; Rogers et al., 2011; Sibley et al., 2014). Accordingly, I investigated how academic achievement and school performance differed over time for adolescents with and without ADHD. Given that many children and adolescents with ADHD have both lower standardized academic achievement scores and school grades than their typically developing peers, I expected that they would have lower levels of academic achievement and school performance in childhood and adolescence. However, because academic achievement remains relatively stable whereas school performance tends to fluctuate, especially during periods of transition, I expected that the patterns of change over time would differ for academic achievement and school performance. More specifically, I expected less decline in academic achievement than in school performance.

Trajectories of Affective Symptoms

Students with ADHD are more likely than their non-ADHD peers to develop anxiety and depression. Both affective conditions are known to have negative associations with academic achievement (e.g., Duchesne et al., 2008; Fröjd et al., 2008; Huang, 2015; Kirkaldy & Siefen, 1998; Singh & Thukral, 2009; Van Ameringen et al., 2003). Among children aged 3-17 years with ADHD, the prevalence rates of anxiety and depression are 37.9% and 32.3%, respectively, compared to 7.1% and 3.2% of children in the general population (Ghandour et al., 2019). Thus, anxiety and depression could be important factors in understanding trajectories of academic achievement, especially in children and adolescents with ADHD.

Few studies have used developmental trajectories to investigate the developmental progression of anxiety and depression (e.g., Copeland et al., 2014; Ferro et al., 2015; Shore et al., 2018; Toumbourou et al., 2011). Copeland et al. (2014) found that anxiety disorders were present in middle childhood (i.e., ages 9-10; 6%), decreased during late childhood (i.e., ages 11-12; 2%) and then steadily increased during mid-adolescence (i.e., ages 15-16; 3%), late adolescence (i.e., age 19; 5.5%), and early adulthood (i.e., ages 24-26; 8.5%). In comparison to anxiety, which has a median age of onset of 11 years, depression tends to appear later, with a median age of onset of 30 years (Kessler et al., 2005). Ferro et al. (2015) identified three trajectories of depressive symptoms: minimal, subclinical, and clinical. Within the minimal group, symptoms were low and quite stable from ages 12-25 years. In contrast, for the subclinical and clinical groups, symptoms increased from early adolescence (i.e., 12-13 years of age) to mid-adolescence (i.e., 16-17 years of age) and then decreased and levelled off in early

adulthood (i.e., 24-25 years of age). Thus, although there is overlap between anxiety and depression, the trajectories appear to differ in the general population.

The median ages of onset for anxiety (*Mdn* = 11) and ADHD (*Mdn* = 7) both occur in childhood, whereas depression onset occurs in adulthood (*Mdn* = 30; Ghandour et al., 2019). Given the later onset of depression, it is possible that anxiety levels will be higher than depression levels in childhood, but as children progress into adolescence, symptoms of depression may emerge, with both disorders having similar trajectories by late adolescence (i.e., ages 17-18). In this thesis, I explored both anxiety and depression in a model that considered the symptoms of the disorders in parallel. This approach allowed me to capture the relations between anxiety and depression – two disorders that are highly comorbid – while also accounting for the differing rates of the disorders in childhood and adolescence.

Although comorbidity between ADHD and anxiety and depression is well-established, the developmental trajectories of anxiety and depression have not been thoroughly explored for people with ADHD. Furthermore, it is worth investigating if the trajectories differ for people with ADHD who eventually enrol in post-secondary education compared to those with ADHD who do not enrol because anxiety and depression have negative associations with academic achievement (e.g., Duchesne et al., 2008; Fröjd et al., 2008; Huang, 2015; Kirkaldy & Siefen, 1998; Singh & Thukral, 2009; Van Ameringen et al., 2003). Thus, in this thesis, I explored whether certain kinds of affective trajectories are related to subsequent post-secondary enrolment.

Enrolment in Post-Secondary Education

People with ADHD are less likely to attend post-secondary education. A recent report from Statistics Canada stated that 77% of Canadians between 18- and 22-years-old who did not have mental health nor neurodevelopmental disorders enrolled in post-secondary education (Arim & Frenette, 2019). In contrast, only 48% with a diagnosed mental health condition enrolled; of that 48%, three-quarters had a diagnosis of ADHD. Are those with ADHD who enrol in post-secondary education different from those with ADHD who do not enrol? To my knowledge, no one has compared the developmental trajectories of adolescents with or without ADHD histories who do or do not eventually enrol in post-secondary studies. I explored ADHD histories and post-secondary enrolment as factors that may shape the developmental trajectories of ADHD symptoms, academic outcomes (i.e., academic achievement and school performance), anxiety symptoms, and depression symptoms. Specifically, through latent curve modelling I:

a) Determined if trajectories of ADHD symptoms differed for adolescents with or without ADHD who did or did not enrol in post-secondary education (Chapter 4).
b) Determined if trajectories of academic outcomes, both academic achievement and school grades, differed for adolescents with or without ADHD who did or did not enrol in post-secondary education (Chapter 5).
c) Determined if trajectories of affective symptoms (i.e., anxiety and depression) differed for adolescents with or without ADHD who did or did not enrol in post-secondary education (Chapter 6).

Can Post-Secondary Enrolment be Accurately Predicted?

As discussed above, longitudinal analyses, such as latent curve modelling, can provide important information about changes that occur over time. However, collecting longitudinal data is both expensive and time-consuming. Additionally, the trajectories do not consider ADHD symptoms, academic outcomes, and anxiety and depression symptoms simultaneously. Thus, in Chapter 7, I trained several different machine learning algorithms, comparing the predictive classification accuracy, to determine whether post-secondary enrolment could be accurately predicted for adolescents with ADHD histories.

In the next chapter, I discuss the existing literature on ADHD with respect to academic outcomes and comorbidity. In Chapter 3, I present the methodology of the MTA study in detail and outline a plan for the analyses used in this thesis, specifically, latent curve modelling, and machine learning. In Chapters 4, 5, and 6, I present the findings of the latent curve modelling analyses for ADHD symptoms, academic outcomes, and anxiety and depression, respectively. In Chapter 7, I present the findings from the machine learning analyses. Finally, in Chapter 8, I discuss the implications of the findings.

CHAPTER 2: LITERATURE REVIEW

Attention-Deficit/Hyperactivity Disorder: An Overview

Attention-deficit/hyperactivity disorder is characterized by a persistent pattern of inattention and/or hyperactivity-impulsivity that interferes with daily functioning and development (American Psychiatric Association, 2013). Within the Fifth Edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), symptoms of the disorder fall into two categories: inattention (n = 9) and hyperactivity/impulsivity (n = 9). Typical symptoms of inattention include failure to give close attention to detail/careless mistakes, difficulty sustaining attention, not listening when spoken to directly, failing to finish tasks, difficulty organizing tasks, and forgetfulness. In contrast, typical symptoms of hyperactivity/impulsivity include excessive fidgeting/tapping/squirming in seat, leaving seat when expected to remain seated, inability to play quietly, blurting out answers before a question is completed, and frequently interrupting others. In general, both the category of symptoms and number of symptoms are used to diagnose ADHD.

According to the DSM-5 (American Psychiatric Association, 2013), diagnoses of ADHD are classified into one of three subtypes: predominantly inattentive (ADHD-I), predominantly hyperactive/impulsive (ADHD-HI), and combined inattentive-hyperactive-impulsive (ADHD-C). A diagnosis of ADHD-I requires at least six symptoms of inattention (five for adults), but fewer than five symptoms of hyperactivity/impulsivity; the reverse is required for a diagnosis of ADHD-HI. For ADHD-C, at least six symptoms (five for adults) from both categories must be present. An estimated 40-65% of children with ADHD will continue to meet the diagnostic criteria for ADHD in adulthood (Barkley et al., 2008; Faraone et al., 2015; Owens et al.,

2015). Many people with childhood ADHD who no longer meet the criteria for ADHD in adulthood continue to be functionally impaired (Hechtman et al., 2016; Sibley et al., 2012). Although ADHD can be diagnosed for the first time in adulthood, symptoms were probably present prior to adolescence (Sibley et al., 2018). Often, if symptoms were not present prior to adulthood then the symptoms can be better explained by substance abuse or a mental disorder other than ADHD.

The presentation of ADHD in adulthood can be different than that in childhood. As children develop, core symptoms shift, with hyperactivity declining by adolescence, impulsivity transforming into more overt executive functioning deficits, and attentional problems remaining more stable (Wasserstein, 2005). As a result of their executive functioning deficits, adults with ADHD are likely to put off important tasks and be disorganized and forgetful (Resnick, 2005). In addition to the symptoms associated with ADHD, adults with ADHD histories are more likely to present with concurrent psychiatric disorders, including antisocial, mood, anxiety, and substance abuse disorders, than non-ADHD adults (Biederman et al., 2004). They are also more likely to have lower collegiate grade-point averages, lower graduation rates, and lower socioeconomic status compared to those without ADHD (Barkley et al., 2006; Mannuzza et al., 1993; Sobanski et al., 2008). Thus, many adults with ADHD histories continue to be functionally impaired. Nonetheless, in their review, Franke et al. (2018) concluded that the predictors of ADHD persistence and the development of comorbid disorders are weak and inconsistent, and that the lifespan perspective on ADHD from childhood to adulthood is missing from the existing literature. Thus, studying how issues related to ADHD, such as

comorbid disorders and academic difficulties, change for children with ADHD could improve prediction of adult outcomes and impairments.

The reported ADHD persistence rates from childhood to adulthood vary across studies, with a review noting that prevalence rates of ADHD beyond adolescence ranged from 4% to 76% (Caye et al., 2016). This level of heterogeneity suggests that there are important factors, many unidentified, that may moderate the persistence of the disorder. This level of heterogeneity also suggests that an emphasis should not be placed on prevalence rates, but rather the focus should shift to understanding functional impairments present in adults with ADHD histories, given that many adults who no longer meet the criteria for ADHD continue to be functionally impaired (Hechtman et al., 2016; Sibley et al., 2012). Based on a meta-analysis, Erskine et al., (2016) concluded that there is a longitudinal association between ADHD histories and adverse outcomes, such as mental disorders and academic underachievement.

Given that mental disorders, including anxiety and depression, and academic underachievement are among the most relevant adverse outcomes, there is a need to further evaluate their developmental trajectories to better understand how these outcomes differ in their development over time for those with and without ADHD. Furthermore, given that people with ADHD who attend post-secondary education have pursued higher education despite being at risk for academic underachievement, comparing the developmental trajectories of those with ADHD histories who do or do not eventually attend post-secondary education may provide valuable insights. For example, it is possible that academic functioning was stable or improving throughout the school years for those with ADHD histories who eventually attended post-secondary studies. In

contrast, perhaps adolescents with ADHD histories who did not go on to post-secondary education experienced not only lower academic achievement, but also decreasing school performance across the school years. Accordingly, in the next section, I discuss the academic outcomes for adolescents with ADHD.

ADHD and Academic Outcomes

Attention-deficit/hyperactivity disorder is typically associated with poor academic performance. In a large study of approximately 4,000 10-year-old children, Czamara et al. (2013) investigated the relation between ADHD symptoms and reading, spelling, and mathematics difficulties. Of all the children sampled, 8.1% presented with ADHD symptoms, with 25% of those with symptoms experiencing reading and spelling difficulties and 6.8% experiencing mathematics difficulties. Thus, children with ADHD symptoms were significantly more likely to present with difficulties in core academic areas than children without ADHD symptoms. In their review, Loe and Feldman (2007) state that, compared to children without ADHD, children with ADHD show significantly lower full-scale IQs; score significantly lower on reading and arithmetic achievement tests; are more likely to repeat a grade, use ancillary services (e.g., tutoring, after-school programs, classroom accommodations), and be placed in special education; and are more likely to be expelled or suspended. Thus, in general, ADHD is associated with poorer academic outcomes, both with respect to standardized academic achievement and school performance.

Longitudinally, symptoms of ADHD tend to decrease in severity but remain present. Approximately 25% of adolescents with ADHD will eventually function comparably to their typically developing peers (Loe & Feldman, 2007). Students with

ADHD who continue to have functional impairments and thus do not catch up to their peers are more likely to fail classes, have lower grades on their report cards in all school subjects, and have lower scores on standardized achievement tests. In general, adolescents with ADHD are less likely to enrol in post-secondary programs; of those who do enrol, fewer complete degree programs in comparison to their typically developing peers (Barkley et al., 2008). Frazier et al. (2007) used meta-analysis to examine the magnitude of achievement problems in children, adolescents, and adults with ADHD and found that on average, persons with ADHD could be expected to obtain a standard score of approximately 89 on measures of achievement, 11 points lower than the general population mean of 100. These findings suggest that there may be more than one trajectory for the academic outcomes of children with ADHD. On the one hand, some children may catch up to their peers, and these are possibly the children who eventually enrol in post-secondary education. On the other hand, there are many children with ADHD who do not catch up to their peers and this might explain why disproportionately many children with ADHD do not eventually enrol in post-secondary education.

Using the MTA data, long-term educational outcomes were compared for adolescents with ADHD histories and a local normative comparison group (LNCG; Hechtman et al., 2016). The majority of people with ADHD histories (61.7%) had a high school degree or less in comparison to only 39.2% of the LNCG. Many of the LNCG had completed at least some college (60.9%) in comparison to only 38.3% of the ADHD group. Adults with ADHD histories were further divided into two groups: symptom-persistent and symptom-desistent. The symptom-persistent group was defined as those who continued to meet the DSM-5 diagnostic criteria for ADHD (i.e., at least five

symptoms of either inattention or hyperactivity/impulsivity reported by either the participant or parent). The symptom-desistent group was defined as those whose symptoms, reported by participant or parent, did not exceed either ADHD domain threshold. Interestingly, when the ADHD group was divided into symptom-persistent and symptom-desistent subgroups, different patterns of educational attainment were found. Specifically, although in comparison to the LNCG (37.1%) both groups were significantly less likely to obtain a bachelor's degree, the symptom-persistent group (8.0%) were significantly less likely to obtain a degree than the symptom-desistent group (17.8%). The heterogeneity of educational outcomes amongst those with ADHD histories again emphasizes the importance of better understanding the developmental trajectories of academic outcomes within the ADHD population and exploring the differences between those who do and do not enrol in post-secondary studies.

To better understand the developmental trajectories of academic outcomes, I considered two measures: academic achievement and school performance. Much of the longitudinal ADHD literature on academic outcomes reports findings from academic achievement tests (Langberg et al., 2011). These tests tend to measure information and skills learned. For typically developing children, academic achievement scores increase slightly over time but at a decreasing rate. Hence, in early years scores are less stable than in later years (Chen et al., 2014; Kowaleski-Jones & Duncan, 1999). With respect to the WIAT, scores are stable over time (Wright, 2010). A second way to measure academic outcomes that has received less attention in the ADHD literature is through academic performance, or school success, using measures of grade, grade retention, and highest level of education completed (Langberg et al., 2011). Similar to standardized measures of

academic achievement, there is a slight increase in grade point average (i.e., GPA) from Grades 1 through 5 (Gutman et al., 2003). However, contrary to standardized academic achievement scores, GPA tends to decrease slightly from Grades 6 through 12 (Gutman et al., 2003). Students also show drops in GPA at transition periods, for example, as they move from elementary to middle or middle to high school (Alspaugh, 1998; Barber & Olsen, 2004). Thus, given that the developmental trajectories are different for academic achievement and school performance, it is likely that the two indices overlap, but are not the same and therefore, it is important to consider both to obtain a more complete picture of the academic outcomes for adolescents with and without ADHD.

Standardized achievement tests and school performance should be considered separately because many skills beyond information learned are needed for school success (Raggi & Chronis, 2006). Although people with ADHD have poorer academic outcomes, with respect to both academic achievement and school grades, the two indices of academic outcomes are related, but separate (Langberg et al., 2011). The correlation between the two indices is significant, but the magnitude is low to moderate, suggesting that academic achievement tests and school performance require different sets of skills. For example, academic achievement deficits in persons with ADHD may be due to difficulties with cognitive functioning, including executive functioning, working memory, and processing speed (Boonstra et al., 2005; Loe & Feldman, 2007). In contrast, poor school performance in persons with ADHD may be linked to failure to listen to classroom instruction, incomplete homework, disorganization, poor study skills, and sloppy work and poor penmanship (Raggi & Chronis, 2006). Given that the two indices

of academic functioning are different, they may not respond to treatment in the same way.

In a systematic-review, a high proportion of studies (75-79%) found that both academic achievement and school performance outcomes were poorer for people with untreated ADHD than non-ADHD controls (Arnold et al., 2020). After receiving ADHD treatment, academic achievement and school performance improved. However, long-term improvements in academic achievement were significantly greater than improvements in school performance. Only 42% of school performance outcomes were reported to improve with treatment in comparison to 79% of academic achievement outcomes. This difference in improvement for standardized achievement versus school performance suggests that not only are academic achievement and school performance different, but that ADHD treatments may not be effectively targeting school performance deficits. Of course, both academic achievement and school performance are important, but school performance is what post-secondary institutions evaluate when making admission decisions. Thus, mapping the developmental trajectories for both academic achievement and academic performance for adolescents with and without ADHD is essential, especially from a post-secondary enrolment perspective.

University students with ADHD have higher ability levels than their peers with ADHD who do not attend university (e.g., Frazier et al., 2007), but nonetheless they are more likely to read course material and textbooks repeatedly to understand the concepts, have difficulty completing timed examinations, and often need to work harder to achieve good grades than students without ADHD (Lewandowski et al., 2008). These students are also less confident in their ability to academically succeed (Blase et al., 2009;

Heiligenstein et al., 1999; Kane et al., 2011; Lewandowski et al., 2008; Shaw-Zirt et al., 2005). Although post-secondary students with ADHD have more academic difficulties than their peers without ADHD, beyond enrolment status, research has not identified how those with ADHD who attend post-secondary education differ from those with ADHD who do not attend post-secondary education. Young people with ADHD histories who attend post-secondary may be symptom-desistent and tend to show stable academic achievement and school performance over time.

I investigated the developmental trajectories of adolescents with or without ADHD who did or did not enrol in post-secondary studies, evaluating academic outcomes and symptom persistence. Given that an increasing number of jobs require some form of post-secondary education, the high prevalence of ADHD, and the large discrepancy in post-secondary enrolment between those with ADHD histories and those without, it is important to identify factors that are related to post-secondary enrolment within the ADHD population so that treatments and accommodations can be designed that help increase a person's likelihood of post-secondary enrolment and success.

Academic performance is related to post-secondary enrolment because admission decisions are often heavily based on a combination of standardized test scores and school grades. But beyond academics, a combination of psychosocial (e.g., mental health, perceived stress, self- concept), situational (e.g., school engagement, parent-child conflict), and socio-demographic factors (e.g., socioeconomic status, geographic location, parental education attainment) are all related to post-secondary enrolment (e.g., Berger & Milem, 1999; Berkner & Cataldi, 2002; Berkner & Choy, 2008; Brown et al., 2008; Chang et al., 2006; Eccles, 2005; Marcenaro-Gutierrez et al., 2007; Parker et al., 2012,

2016; Porchea et al., 2010; Robbins et al., 2004, 2006; Suldo et al., 2018). Thus, many factors beyond intelligence and academic achievement are involved in school performance and enrolment. To better unravel how adolescents with ADHD histories who attend post-secondary differ from those who do not, exploration beyond ADHD symptoms and academic outcomes is necessary. Erskine and colleagues (2016) noted that in addition to academic underachievement, a longitudinal association exists between ADHD and mental disorders. Two mental disorders that are highly comorbid with ADHD are anxiety and depression.

ADHD, Comorbid Affective Disorders, and Academic Outcomes

Relations between Anxiety and Depression: An Overview

Anxiety disorders are the most prevalent of all mental disorders, with approximately 34% of people experiencing an anxiety disorder during their lifetime (Bandelow & Michaelis, 2015). In childhood and adolescence, anxiety disorders are estimated to affect approximately 7% of the population (Ghandour et al., 2019). Anxiety is particularly prominent in university students with approximately 42% of students who seek counselling services reporting anxiety symptoms (Mistler et al., 2012). Anxiety symptoms are normal and experienced by all at some point in time, but when the symptoms become overwhelming and begin to interfere with daily functioning, anxiety reaches a clinical level where it is classified as a disorder (American Psychiatric Association, 2013). The DSM-5 identifies several different anxiety disorders: separation anxiety, selective mutism, social anxiety, specific phobia, panic disorder, agoraphobia, and generalized anxiety disorder. All of these disorders share features of excessive fear and worry.

Anxiety disorders can be chronic, meaning that people may have the disorder for many years, but they are also episodic (Bandelow & Michaelis, 2015). In other words, a person may develop an anxiety disorder in childhood, adolescence, or adulthood, but over time, especially for those who seek psychological treatment, the symptoms may lessen or disappear, and the person will no longer meet the criteria for a clinical disorder. For many, anxiety disorders peak around middle age and then decrease in older age. Even without treatment, anxiety disorders do not tend to last into late adult years, with very low prevalence rates being reported in persons between the ages of 65 to 79 years (Jacobi et al., 2014).

Depression is the leading cause of disability around the world (Friedrich, 2017). In recent decades, the prevalence of depression and depressive symptoms have increased (Vos et al., 2016). The lifetime prevalence rates of depression are estimated to be 20-25% for women and 7-12% for men (World Health Organization, 2002). In childhood and adolescence, depression is estimated to effect approximately 3% of the population (Ghandour et al., 2019). Similar to anxiety, depression is a leading mental health concern among university students, with approximately 36% of students who seek counselling services reporting depressive symptoms (Mistler et al., 2012). Although it is normal for people to feel sadness, people with depression experience such intense sadness and hopelessness that it interferes with their daily functioning. Symptoms of depression can include diminished interest or pleasure in all or most activities, weight loss or weight gain, fatigue or loss of energy, feelings of worthlessness, and a diminished ability to concentrate (American Psychiatric Association, 2013).

Similar to anxiety, depression can be chronic, but episodic. Unlike anxiety, clinical depression is quite rare in childhood, with children under the age of 12 years presenting with few depressive symptoms (Toumbourou et al., 2011). Adolescents are especially at risk for suicide attempts in comparison to children and adults (Rohde et al., 2013), but the highest prevalence rates of depression are seen in emerging adulthood and adulthood (Kim-Cohen et al., 2003; Rohde et al., 2013). Because depression is episodic, symptom severity may vary across childhood, adolescence, and adulthood (Shore et al., 2018). Researchers have suggested that depression be considered on a continuum of symptom severity; people with depression are symptomatic approximately 60% of the time, typically at the low or subthreshold levels (Judd & Akiskal, 2000).

Depression and anxiety are both considered internalizing disorders (American Psychiatric Association, 2013). Internalizing disorders consist of problems related to worry, sadness, shyness, and self-esteem (Ollendick et al., 2005). Both anxiety and depression can lead to significant functional impairment (e.g., Kendall et al., 2010). Anxiety and depression often co-occur, especially in children and adolescents (e.g., Essau, 2008; Garber & Weersing, 2010). Anxiety has an earlier age of onset than depression; in cases of comorbidity, anxiety is often diagnosed prior to depression (Pollack, 2005; Wittchen et al., 2000). In general, it is estimated that the comorbidity between the two disorders may be as high as 60% (Kaufman & Charney, 2000).

Comorbidity Between ADHD and Internalizing Disorders

Internalizing disorders co-occur in approximately 25-40% of persons with ADHD (MTA Cooperative Group, 1999b; Tannock, 2009). Children with ADHD are more likely to have more than one anxiety disorder (27%) than their typically developing peers (5%;

Schatz & Rostain, 2006). Similarly, the lifetime prevalence of depression is estimated to be 5.5 times higher in persons with ADHD than those without ADHD (Angold et al., 1999).

One hypothesis about the comorbidity of ADHD and these disorders is that problems associated with ADHD are exacerbated in the presence of anxiety and depression because cognitive difficulties are compounded with emotional difficulties (Bubier & Drabick, 2009). Another view posits that internalizing disorders may differentiate persons with symptom-persistent and symptom-desistent ADHD (Biederman et al., 1996). Testing these hypotheses requires longitudinal studies, however, there is limited research examining the developmental trajectories of ADHD and comorbid disorders.

In a study that examined the developmental trajectories of ADHD symptoms from Grades 3 through 12, three trajectory classes were identified: low (i.e., consistently low levels of symptoms), declining (i.e., symptoms decreasing over time), and high (i.e., consistently high levels of symptoms; Sasser et al., 2016). Emotional difficulties were significantly different across the three trajectories, with the low trajectory class experiencing significantly less emotional distress and dysregulation than the declining and high trajectory classes, and the declining trajectory class experiencing significantly less emotional distress and dysregulation than the high trajectory class. Sasser et al. concluded that emotional difficulties may need more attention in ADHD treatment models given their association with differential developmental trajectories.

To my knowledge, only one study (Meinzer et al., 2016) has examined the developmental trajectories of internalizing disorders, specifically depressive symptoms,

in a sample of emerging adults with and without ADHD. In this longitudinal study, the rate of change in depressive symptoms did not differ for persons with or without ADHD from ages 18 through 25. However, persons with a childhood history of ADHD had significantly higher levels of depressive symptoms at all ages of emerging adulthood. Childhood ADHD continued to predict depressive symptoms after controlling for comorbid diagnoses, but not when controlling for ADHD symptom severity and psychosocial impairment. These findings suggest that by late adolescence, emerging adults with ADHD histories have more symptoms of depression, and the symptoms are persistently higher over time.

In summary, there is some limited evidence that, during adolescence, changes occur which lead to changes in symptom presentation as adolescents with ADHD make the transition to adulthood. More information is needed, however, about the nature of these changes, when they occur, and how anxiety and depression may influence those changes. Thus, I examined the developmental trajectories of internalizing disorders, addressing absences in the literature pertaining to the development of comorbid disorders in ADHD and how this development may differ for adolescents who did and did not attend post-secondary education.

Similar to considering how academic outcomes are measured, in this thesis I carefully considered how anxiety and depression were measured. Given the high comorbidity between anxiety and depression, both in the general population and in the ADHD population, I considered why the disorders may share such high comorbidity and how best to measure the symptoms of these disorders.

One possible reason for the high co-occurrence of anxiety and depression is the overlap in symptoms. For example, thought ruminations present in depression are similar to the overthinking and worry seen in anxiety, and the energy loss and fatigue in depression are similar to the fatigue associated with specific phobias, a type of anxiety disorder. Two common indices used to measure anxiety and depression symptoms in adults are the Beck Anxiety Inventory (Beck & Steer, 1993) and the Beck Depression Inventory-II (Beck et al., 1996). In an exploratory factor analysis of the two inventories (Lee et al., 2018), the items from the two inventories did not load onto two separate factors. Instead, five factors were found that explained 56% of the total variance, with some factors containing items from each inventory. This finding suggests that anxiety and depression are not easily distinguished.

Given the high comorbidity not only between anxiety and depression but among many mental disorders, researchers have suggested that a transdiagnostic approach to mental illness may be required (Dalgleish et al., 2020). From the transdiagnostic view, traditional approaches are thought to impose symptoms into artificial categories, sacrificing the richness of clinical information available. For example, clinical thresholds are set arbitrarily, even though many people with subclinical symptom thresholds experience functional impairments, and considerable heterogeneity is present within diagnoses. These arbitrary thresholds are of particular importance when considering adults with ADHD histories, as many will no longer meet the clinical criteria for ADHD in adulthood but will continue to experience functional impairment. Thus, it is possible that the DSM-5 criteria are not sensitive enough to adequately classify persons with ADHD in adulthood (Barkley et al., 2002). The same issue of sensitivity may be true

when considering the persistence of symptoms within internalizing disorders. Thus, according to the transdiagnostic approach, clinicians should consider the symptoms present in clients and develop underlying treatment principles that can effectively treat a range of mental disorders rather than developing protocols for specific diagnoses. From the transdiagnostic perspective, anxiety and depression are not separate disorders. Instead, the symptoms present in each individual would be evaluated on a continuum, setting diagnostic classifications aside.

Overall, there is significant evidence to suggest that anxiety and depression are prominent mental disorders and negatively impact daily functioning. Whether anxiety and depression truly represent two distinct disorders or whether they should be considered together is debatable. However, important to the present study, anxiety and depression tend to have different ages of onset and the impact that symptoms of each disorder can have on a person can vary drastically. Furthermore, the need for developmentally sensitive distinctions between anxiety and depression has been well established (Zahn-Waxler et al., 2000). Thus, consistent with the current distinctions between anxiety and depression set in the DSM-5 (American Psychiatric Association, 2013) and in accordance with the measures used to assess anxiety and depression symptoms in the MTA, I considered anxiety and depression separately, but I modelled their trajectories in parallel so that correlations among the two disorders at each age could be considered.

ADHD, Comorbidity, and Academic Outcomes

Depression, anxiety, and ADHD are all associated with negative life outcomes. One area of particular importance in childhood and adolescence is academic outcomes.

Anxiety disorders can negatively influence a child's school experience, especially in the long-term. Children who exhibited signs of anxiety in kindergarten were more likely to have academic issues at the end of their first year of high school (Duchesne et al., 2008). Adolescents with anxiety are more likely to leave school prematurely, are more likely have lower grades, and are at an increased risk for academic underachievement (Duchesne et al., 2008; Singh & Thukral, 2009; Van Ameringen et al., 2003; Woodward & Fergusson, 2001). However, anxiety is quite prevalent in post-secondary students (Eisenberg et al., 2009), a population we often associate with academic success. Similarly, anxiety is not uncommon among gifted children and adolescents (Guignard et al., 2012). The relationship between anxiety and academic achievement is complex, as different groups of people may be affected by anxiety differently. Thus, my thesis provides insights into whether people who attend post-secondary studies have higher rates of anxiety in childhood and adolescence, prior to post-secondary enrolment, or whether anxiety is more prevalent in those who do not attend post-secondary studies, who may struggle with academic achievement and school performance.

Depression also has negative associations with academic achievement. The symptoms of depression, which include difficulty concentrating, loss of interest in activities, feelings of helplessness and worthlessness, and social withdrawal, negatively influence cognitive performance, and lead to impairments in learning and overall academic achievement (Beck, 1967; Hammen, 1998; Kirkaldy & Siefen, 1998; Kovacs & Goldston, 1991). Adolescents who self-reported clinical levels of depression were more likely to have lower grade point average or greater declines in grade point average from the previous school term (Fröjd et al., 2008). However, similar to anxiety, depression is

quite prevalent among university students (e.g., Barker et al., 2018; Cooke et al., 2006; Eisenberg et al., 2009; Ibrahim et al., 2013; Twenge et al., 2010) and prevalence rates are high in academically achieving individuals, such as those enrolled in advanced placement courses, international baccalaureate programs, medical school, law school, and graduate studies (e.g., Dammeyer & Nunez, 1999; Dyrbye et al., 2006; Evans et al., 2018; Rotenstein et al., 2016; Suldo et al., 2018). Thus, my thesis provides insights into whether adolescents who eventually attend post-secondary studies have higher rates of depression in childhood and adolescence, prior to post-secondary enrolment, or whether depression is more prevalent in those who do not attend post-secondary studies, who may struggle with academic achievement and school performance.

Given the potentially negative associations between anxiety and academic outcomes and depression and academic outcomes, we would expect that some students experiencing internalizing disorders will be more likely to have poorer academic outcomes or more difficulty completing high school. This might be especially true for students with ADHD because not only are they more likely to have comorbid internalizing disorders, but in addition to potential emotional challenges they are also struggling with cognitive challenges.

With respect to how ADHD and comorbid internalizing disorders relate to academic outcomes, findings are mixed. When studied together and classified as internalizing symptoms, anxiety and depression predicted academic underachievement in youth with ADHD who were followed from ages 4 through 14 (Massetti et al., 2008). Separately, it has been suggested that depression, but not anxiety, is related to homework problems in children with ADHD (Karustis et al., 2000). Similarly, depressive symptoms,

not anxiety symptoms, were found to negatively correlate with grades (Alva & de los Reyes, 1999). However, some studies have found no moderating effects of depression or anxiety symptoms on academic performance and suggest that ADHD symptoms are so strongly associated with academic impairment that the co-occurrence, or lack thereof, of internalizing symptoms is unlikely to moderate or exacerbate this relation (Becker et al., 2014; Biederman et al., 1996). In summary, there is no consensus on how anxiety and depression relate to academic achievement in the ADHD population. One possible reason for this lack of consensus is the heterogeneity among people with ADHD.

People with ADHD are heterogeneous with respect to symptom persistence, comorbidity, and academic outcomes. For example, in the MTA, when the ADHD group was compared to the LNCG at the 16-year follow up, rates of internalizing disorders did not differ between the two groups. However, when the ADHD group was divided into symptom-persistent and symptom-desistent subgroups, the symptom-persistent subgroup had higher rates of internalizing disorders than the symptom-desistent subgroup, who did not significantly differ from the LNCG (Hechtman et al., 2016). Thus, it is important to consider different groups within the ADHD population and compare developmental trajectories among different groups to cultivate an understanding of if and when groups may differ.

One subgroup to consider is adolescents with ADHD who eventually enrol in post-secondary studies. One possibility is that this group has lower levels of anxiety and depression than their ADHD peers who did not attend post-secondary education because they have presumably had some academic success. However, findings for post-secondary students with ADHD concerning the prevalence of anxiety and depression are mixed.

There are three views to consider. From the first view, persons who attend post-secondary education may have lower levels of anxiety or depression in childhood and adolescence than those who do not attend post-secondary education. In line with this view, some studies have found that people with ADHD had greater academic impairments than their typically developing peers, but there were no differences between the two groups on measures of anxiety and depression, and anxiety and depression did not appear to be negatively related to academic performance above and beyond a diagnosis of ADHD (Heiligenstein et al., 1999; Nelson & Gregg, 2012). Thus, from this view, adolescents with ADHD histories who eventually attend post-secondary studies should have similar developmental trajectories of anxiety and depression than their non-ADHD peers who attend post-secondary education.

From the second view, persons with ADHD who attend post-secondary education may have higher levels of anxiety and depression in childhood and adolescence than their non-ADHD peers. Supporting this view, some studies have found that post-secondary students with ADHD histories reported more depressive symptoms than their non-ADHD peers (Blase et al., 2009; Rabiner et al., 2008). The causality may be that post-secondary students with ADHD tend to have better coping skills and fewer cognitive impairments than students with ADHD who do not attend post-secondary education (Glutting et al., 2005), but they still continue to face impairments that their non-ADHD peers do not. On this view, because those who attend post-secondary education have had more academic success and are more resilient, they had fewer symptoms of anxiety and depression than their peers who did not attend. However, even with academic success in elementary and high school, the cognitive deficits associated with ADHD may lead to more symptoms of

anxiety and depression in post-secondary students with ADHD compared to their non-ADHD peers. Thus, from this view, adolescents who eventually attend post-secondary studies should have lower levels of anxiety or depression in childhood and adolescence than those who do not attend. Furthermore, within the post-secondary group, adolescents with ADHD histories should have higher levels of anxiety or depression in childhood and adolescence than their non-ADHD peers.

From the third view, persons who attend post-secondary education may have higher levels of anxiety or depression in childhood and adolescence than those who do not attend post-secondary education. In line with this view, some studies have found that post-secondary students are especially at risk for anxiety and depression (Barker et al., 2018; Cooke et al., 2006; Ibrahim et al., 2013; Twenge et al., 2010). Even before post-secondary enrolment, high-achieving students have been found to be at risk for anxiety and depression (Guignard et al., 2012; Suldo et al., 2018). Thus, from this view, adolescents who eventually enrol in post-secondary studies should have higher levels of anxiety or depression in childhood and adolescence than those who do not attend post-secondary education.

Overall, there are many plausible trajectories with respect to both academic outcomes and internalizing disorders for adolescents with or without ADHD who do or do not eventually attend post-secondary education. There is limited longitudinal research available, and to my knowledge none that has examined developmental differences in adolescents with ADHD who enrol in post-secondary education and adolescents with ADHD who do not enrol. Thus, this thesis addresses this gap in the literature to try and

provide a more complete picture of ADHD in childhood and adolescence and how it may relate to future post-secondary enrolment.

Present Research

The goal of this thesis was to determine if and when ADHD symptoms, academic outcomes, and symptoms of internalizing disorders differed for four groups: adolescents with ADHD histories and eventual post-secondary enrolment (ADHD Post-Secondary), adolescents with ADHD histories but without post-secondary enrolment (ADHD No Post-Secondary), adolescents without ADHD histories but with post-secondary enrolment (LNCG Post-Secondary), and adolescents with neither ADHD histories nor post-secondary enrolment (LNCG No Post-Secondary). Using latent curve modelling, I modelled developmental trajectories of ADHD symptoms (Chapter 4), academic achievement (Chapter 5), and anxiety and depression symptoms (Chapter 6), comparing the four groups. In Chapter 7, I use machine learning to determine if models could accurately predict post-secondary enrolment for adolescents with ADHD histories.

ADHD Symptoms

Research Question

Do the trajectories of ADHD symptoms differ for the four groups of adolescents, that is, those with or without ADHD histories who did or did not attend post-secondary education?

Hypotheses: ADHD Symptoms

There were many different possible trajectories for each of the four groups. Based on a review of the literature, I focused on probable patterns.

I expected levels of ADHD symptoms to be higher overall for adolescents with ADHD histories (i.e., ADHD Post-Secondary and ADHD No Post-Secondary) than those without ADHD histories (i.e., LNCG Post-Secondary and LNCG No Post-Secondary). Among adolescents with ADHD histories, I expected symptoms to be especially high for those who did not eventually enrol in post-secondary studies, as I hypothesized that functional impairments due to persisting symptoms may have acted as a barrier for post-secondary enrolment.

For the LNCG, given that all participants in the LNCG were screened for ADHD and those who met the criteria were removed from analyses, there were two plausible symptom levels. The first was that both the LNCG Post-Secondary and LNCG No Post-Secondary would have similar levels of symptoms because they had no history of ADHD and they were unlikely to have significant symptoms of ADHD. The second was that symptom levels would be slightly higher for the LNCG No Post-Secondary than the LNCG Post-Secondary. Many of the symptoms of ADHD are related to executive functioning, such as making careless mistakes, being unable to pay attention during boring or repetitive work, and procrastination, so it is possible that difficulties with executive-function tasks, resulting in behaviours that align with some symptoms of ADHD, would be more evident in the LNCG No Post-Secondary. These difficulties may result in worse academic performance and thus less opportunity or interest in post-secondary enrolment (Combs et al., 2015; Kwon et al., 2018; Richardson et al., 2012).

The model was tested as a piecewise model permitting a knot (inflection point) at age 13 because I anticipated two different linear slopes: ages 9-13 and ages 13-17. The knot was placed at age 13 because the literature suggests that symptoms of ADHD tend

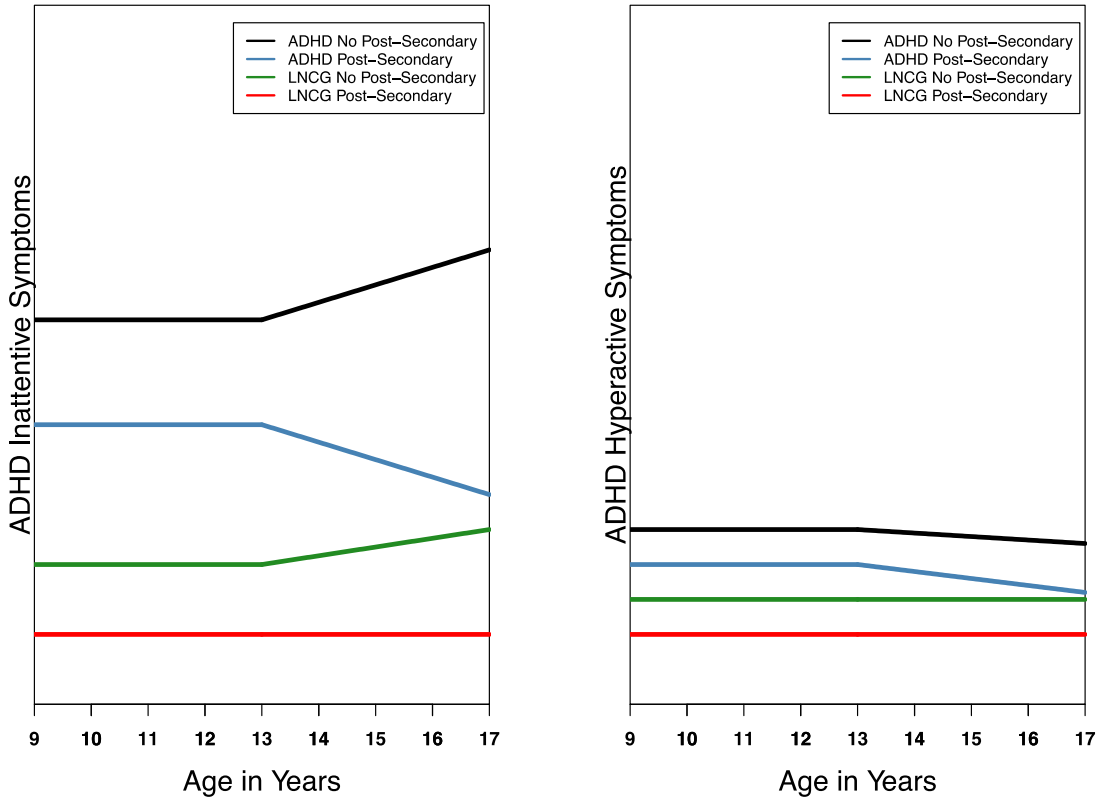
to decrease in adolescence, with approximately 25% of adolescents with ADHD histories functioning comparably to their typically developing peers (Loe & Feldman, 2007). Furthermore, by adolescence, the hyperactive symptoms of ADHD are often no longer present and thus there may be an overall decline in ADHD symptoms (Wasserstein, 2005).

For all four groups, I anticipated relatively flat slopes from ages 9-13. The MTA research has shown that ADHD symptoms decline precipitously over the course of treatment. However, symptoms do not usually completely disappear, but rather may present at a subclinical level, hence why I predicted level differences but not slope differences across the four groups. By Year 2, participants with ADHD had completed treatment. Thus, I anticipated relatively stable trajectories of symptomology in late childhood.

From ages 13-17 I anticipated that the prevalence of symptoms for the ADHD Post-Secondary group would decline, as they begin to function comparably to their typically developing peers (Loe & Feldman, 2007). Similarly, for the LNCG, I anticipated relatively flat slopes across all ages as these individuals had no ADHD histories so a significant increase or decrease in symptoms would not be expected. In contrast, for the ADHD No Post-Secondary group, I anticipated the prevalence of symptoms would remain relatively flat or possibly increase, on the assumption that their symptoms would persist into adolescence and possibly early adulthood, as shown in previous MTA research (Hechtman et al., 2016; Howard et al., 2016). See Figure 2.1 for hypothesized trajectories.

Figure 2.1

Hypothesized Trajectories of ADHD Symptoms from Ages 9 through 17



Academic Outcomes

Research Question

Do the trajectories of academic outcomes differ for the four groups of adolescents, that is, those with or without ADHD histories who did or did not attend post-secondary education? Separate trajectories were modelled for each of the following:

i) Each composite score for reading, spelling, and mathematics (three models) from the WIAT

ii) Overall GPA

iii) Subject grades for mathematics and English (i.e., reading, writing, language)

Hypotheses: Academic Achievement

I expected levels of academic achievement to be higher for the two groups who eventually enrolled in post-secondary studies (i.e., ADHD Post-Secondary and LNCG Post-Secondary) than the two groups who did not eventually enrol (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary).

Within the post-secondary groups, I anticipated that the LNCG Post-Secondary would have higher academic achievement than the ADHD Post-Secondary group because adolescents with ADHD histories who eventually attend post-secondary studies tend to have lower academic achievement and continue to have more academic difficulties in post-secondary education than their typically developing peers (Frazier et al., 2007; Green & Rabiner, 2012; Lewandowski et al., 2008).

For the non-post-secondary groups, I anticipated the LNCG No Post-Secondary would have higher academic achievement than the ADHD No Post-Secondary group

because adolescents in the LNCG do not have a history of ADHD and ADHD is associated with significant deficits in academic achievement (Czamara et al., 2013; Frazier et al., 2007; Loe & Feldman, 2007).

For adolescents with no history of ADHD, academic achievement is a strong predictor of university enrolment, thus I predicted the LNCG Post-Secondary would have higher academic achievement than the LNCG No Post-Secondary. Furthermore, for the ADHD Post-Secondary group I predicted higher academic achievement than the ADHD No Post-Secondary group as these individuals tend to have better academic success in primary and secondary school (Frazier et al., 2007).

Given the stability of standardized academic achievement, I anticipated the trajectories would be similar across reading, spelling, and mathematics, especially because children with ADHD tend to have deficits in all core academic areas (Czamara et al., 2013; Dupaul et al., 2013; Frazier et al., 2007). Furthermore, while treatment can improve academic achievement in persons with ADHD (Arnold et al., 2020), the majority of participants with ADHD received treatment prior to the Year 2 follow-up, so it is unlikely that the ADHD Post-Secondary and ADHD No Post-Secondary groups would differ because of access to treatment. Because academic achievement is a stable construct (Chen et al., 2014; Kowaleski-Jones & Duncan, 1999; Wright, 2010), I anticipated relatively flat slopes for each of the four groups for reading, mathematics, and spelling achievement. Thus, a linear latent curve model was selected.

Hypotheses: School Performance

Similar to academic achievement, I expected that the two groups who eventually enrolled in post-secondary studies (i.e., ADHD Post-Secondary and LNCG Post-

Secondary) would have better school performance than the two groups who did not eventually enrol (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary). I anticipated the same pattern for overall GPA, mathematics, and English grades.

Contrary to academic achievement, I did not anticipate steady slopes for each of the four groups because more factors influence school performance than academic achievement, such as classroom climate, student behaviour in the classroom, and school attendance (Duckworth et al., 2012; Horner et al., 2009; Reyes et al., 2012); school performance did not improve for as many of the persons with ADHD histories in the MTA after treatment (42%) as did academic achievement (79%; Arnold et al., 2020) and school performance tends to be sensitive to periods of transition, such as moving from middle school to high school (Alspaugh, 1998; Barber & Olsen, 2004; Gutman et al., 2003). Thus, a piecewise model was specified with the knot placed at Grade 8.

For the LNCG (i.e., LNCG Post-Secondary and LNCG No-Post Secondary) I anticipated a relatively flat slope from Grades 6 through 8 (Gutman et al., 2003). From Grade 8 to 9, I anticipated that the LNCG would experience a decline in grades as they transitioned to high school (Alspaugh, 1998; Barber & Olsen, 2004). I anticipated a less stable trajectory for school performance in comparison to academic achievement because many skills are needed for school success beyond just information learned (Raggi & Chronis, 2006).

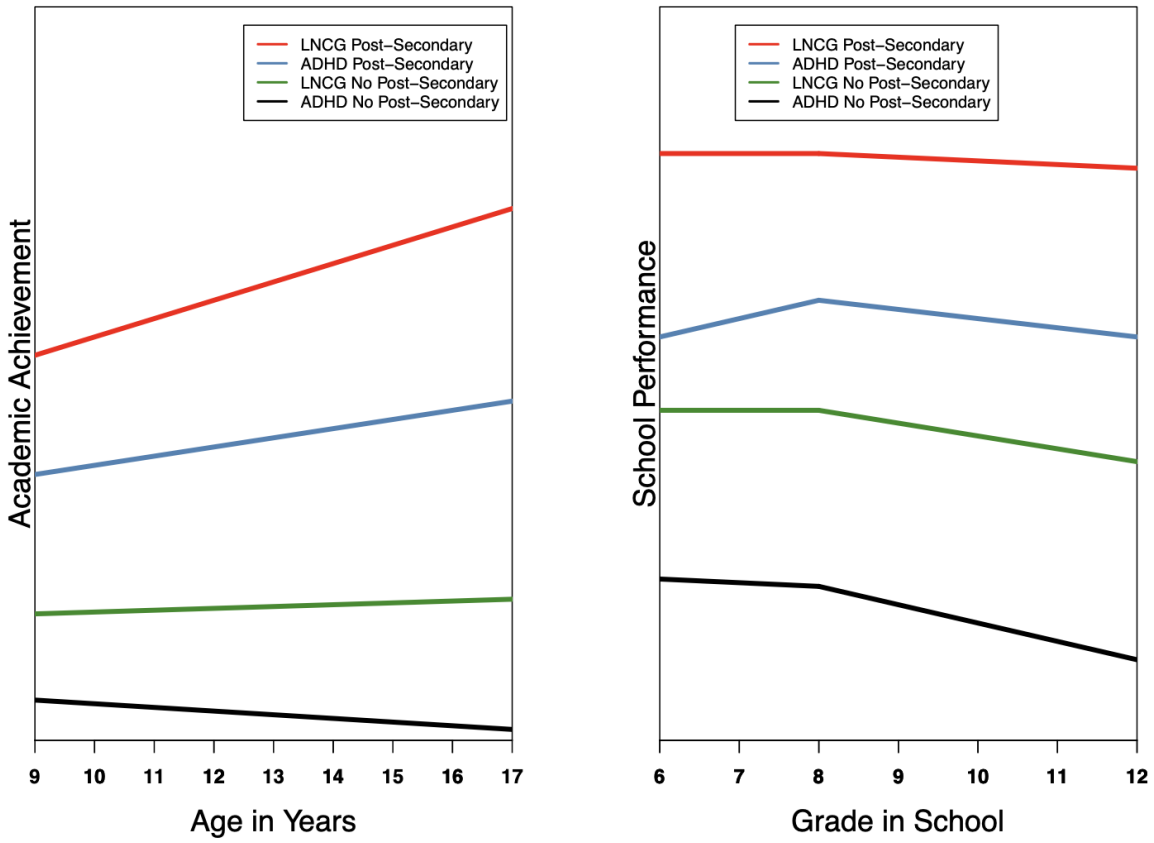
For the ADHD Post-Secondary group, I anticipated a slight increase in school grades from Grades 6 to 8, as it is possible that this group includes the adolescents described in Arnold et al. (2020) whose school grades improved after treatment. From grades 8 to 12, I anticipated similar slopes to the LNCG Post-Secondary, albeit with

slightly weaker school performance (i.e., lower intercepts). As discussed previously, I hypothesized that this group would be ADHD symptom-desistent and thus by adolescence they may be functioning similarly to their peers (Loe & Feldman, 2007). However, even among the high achieving people with ADHD histories there are still school related challenges. For example, post-secondary students with ADHD are more likely to reread course material to understand concepts and struggle to complete timed examinations (Lewandowski et al., 2008). Thus, I anticipated that their overall school performance would still be worse than the LNCG Post-Secondary. Given that deficits are not subject specific for people with ADHD, I did not anticipate different trajectories for different school subjects.

For the ADHD No Post-Secondary group, I anticipated a slight decline in school performance from Grades 6 through 8 and then a more dramatic decline from Grades 8 through 12. This group is more likely to be ADHD symptom-persistent than the ADHD Post-Secondary group (Hechtman et al., 2016) and thus I did not anticipate that they would catch up to their typically developing peers (i.e., the LNCG). Adolescents with ADHD histories who do not catch up to their peers are more likely to fail classes and have lower grades in all subjects (Loe & Feldman, 2007). Furthermore, given that transition periods are difficult for youth in general (Alspaugh, 1998; Barber & Olsen, 2004) and that the high school environment requires students to be more independent, as well as having higher levels of challenge and competition, it is possible that the coping strategies used by the ADHD No Post-Secondary group would no longer be effective in high school, which could negatively influence school performance. See Figure 2.2 for hypothesized trajectories for academic achievement and school performance.

Figure 2.2

Hypothesized Trajectories of Academic Achievement from Ages 9 through 17 and School Performance from Grades 6 through 12



Anxiety and Depression

Research Questions

Do the trajectories of anxiety and depression symptoms differ for the four groups of adolescents, that is, those with or without ADHD histories who did or did not attend post-secondary education?

Are there level differences in anxiety and depression when students transition from childhood to adolescence?

Is growth in anxiety related to growth in depression in adolescents with or without ADHD?

Hypotheses: Anxiety and Depression

Groups could be changing in multiple ways. Below, I outline probable trajectories. For each of the hypothesized trajectories I anticipated modelling using piecewise latent curve modelling with the knot at age 13. I anticipated the knot would be at age 13 because the literature suggests that symptoms of anxiety and depression tend to increase around puberty/adolescence (e.g., Copeland et al., 2014; Ferro et al., 2015; Kessler et al., 2001, 2005; Toumbourou et al., 2011). Within the parallel model, I anticipated that depression intercepts would be lower than anxiety intercepts at the knot because the onset of depression tends to occur later than the onset of anxiety (Shore et al., 2018; Toumbourou et al., 2011). For all four groups and all hypothesized trajectories outlined below, I anticipated relatively flat slopes from ages 9-13 with minimal symptoms of depression present during this time as children present with few depression symptoms prior to age 12 (Toumbourou et al., 2011) and any symptoms of anxiety and

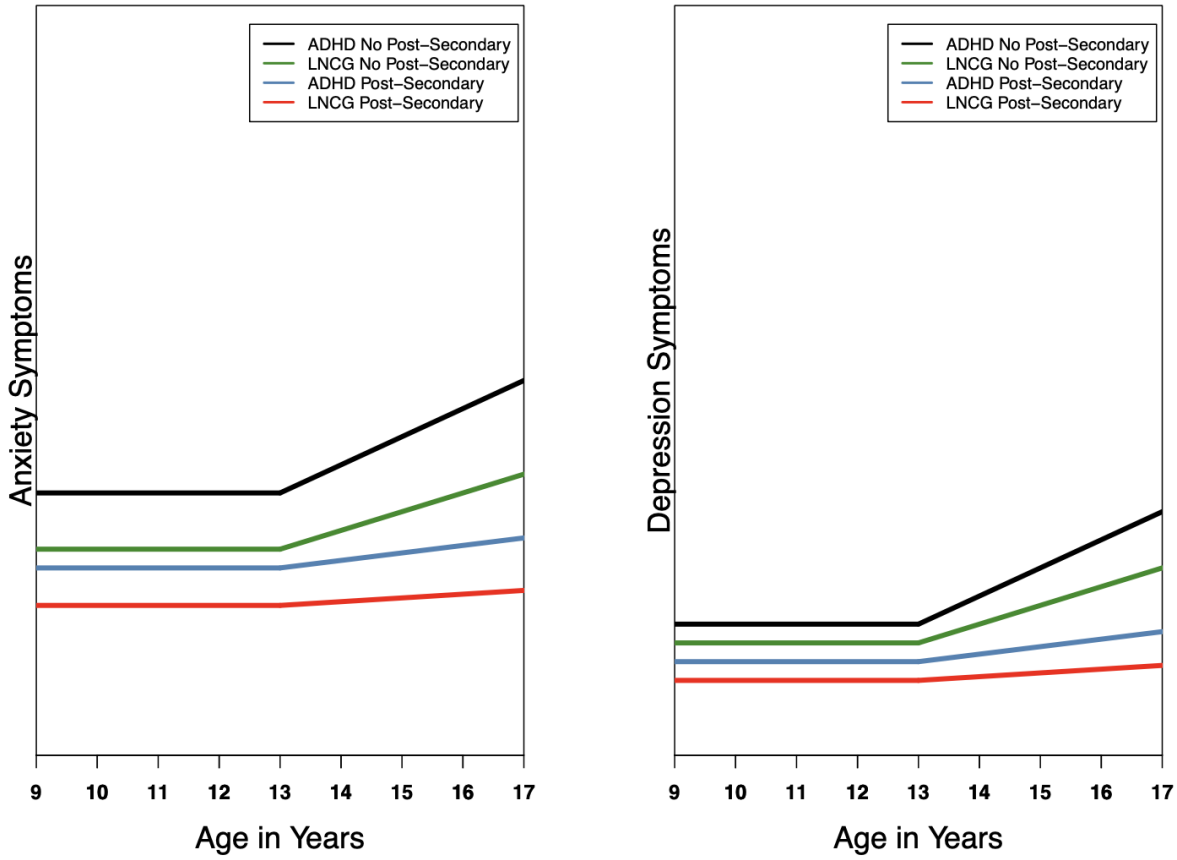
depression that are present tend to be relatively stable during these years (Copeland et al., 2014).

Hypothesis I. One possibility was that the groups who did not enrol in post-secondary studies (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary) would report the highest levels of anxiety and depression at 13 years and the post-secondary groups (i.e., ADHD Post-Secondary and LNCG Post-Secondary) would report the lowest levels. Some of the literature states that anxiety and depression are negatively related to academic achievement (e.g., Beck, 1967; Duchesne et al., 2008; Hammen, 1998; Kirkaldy & Siefen, 1998; Singh & Thukral, 2009; Van Ameringen et al., 2003). If this is the case, then this would be evident in greater levels of anxiety for the non-post-secondary groups than for the post-secondary groups.

With respect to slopes, I expected that from ages 13-17 all groups would experience an increase in anxiety and depression symptoms because adolescence can be a stressful time for many. I expected a greater increase in symptoms (i.e., steeper positive slope) for the non-post-secondary groups than for the post-secondary groups because some of the literature suggests that poor school performance can lead to increased symptoms of internalizing disorders (Huang, 2015). In contrast, the post-secondary groups could have stable or slightly increasing anxiety and depression symptoms as they were less likely to be struggling academically. See Figure 2.3 for hypothesized trajectories.

Figure 2.3

Hypothesized Trajectories (Hypothesis I) of Anxiety and Depression Symptoms from Ages 9 through 17

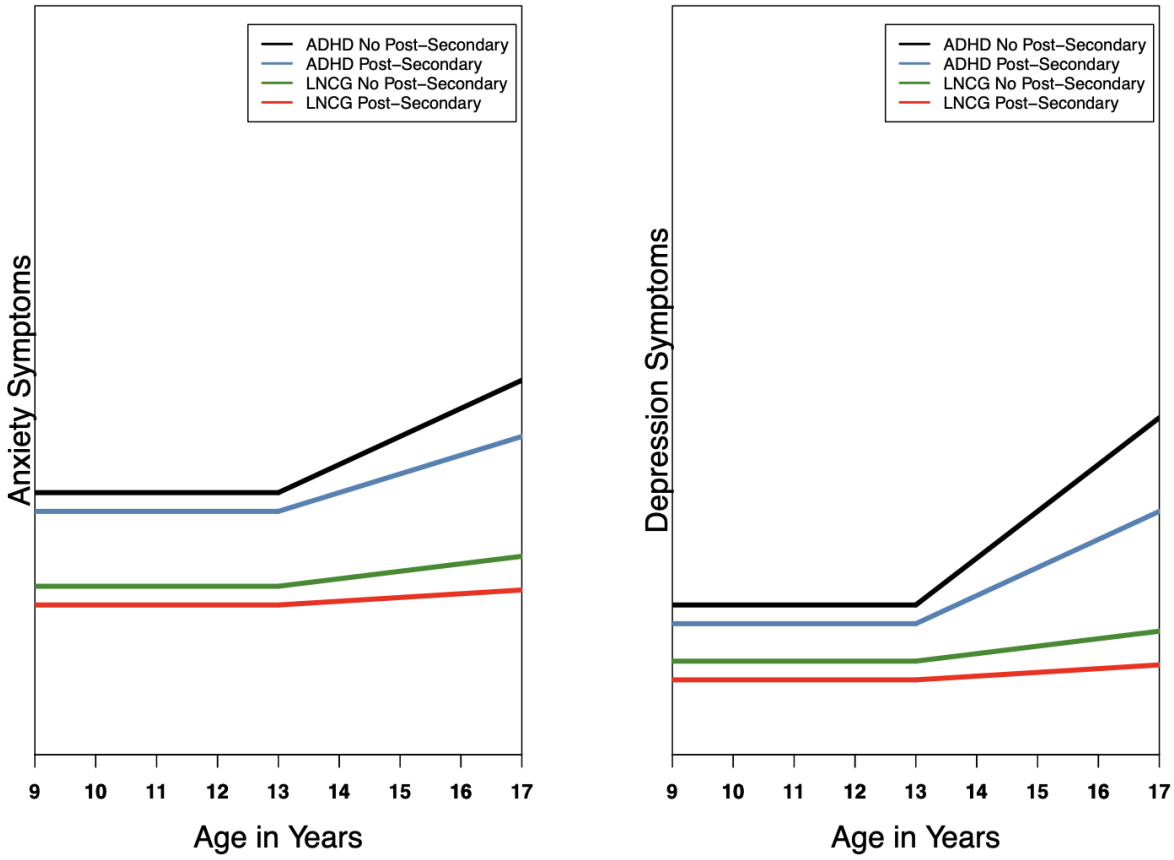


Hypothesis II. A second possibility was that the two ADHD groups (i.e., ADHD Post-Secondary and ADHD No Post-Secondary) would have greater anxiety and depression than the LNCG (i.e., LNCG Post-Secondary and LNCG No Post-Secondary). Anxiety and depression are more prominent in adolescents with ADHD than among typically developing peers (Angold et al., 1999; MTA Cooperative Group, 1999b; Schatz & Rostain, 2006; Tannock, 2009), thus it was possible that those students with ADHD histories would report more anxiety and depression than those without ADHD, independent of eventual post-secondary enrolment.

With respect to slopes, I anticipated a greater increase in symptoms (i.e., steeper slope) for the ADHD groups than the LNCG from ages 13-17. Students with ADHD histories report more symptoms of internalizing disorders than their non-ADHD peers (Blase et al., 2009; Rabiner et al., 2008) and the frequency of symptoms of internalizing disorders predicted underachievement in youth with ADHD (Massetti et al., 2008). Thus, the ADHD groups could be particularly vulnerable to anxiety and depression, and the many changes and transitions that occur during adolescence could result in increasing symptoms. See Figure 2.4 for hypothesized trajectories.

Figure 2.4

Hypothesized Trajectories (Hypothesis II) of Anxiety and Depression Symptoms from Ages 9 through 17



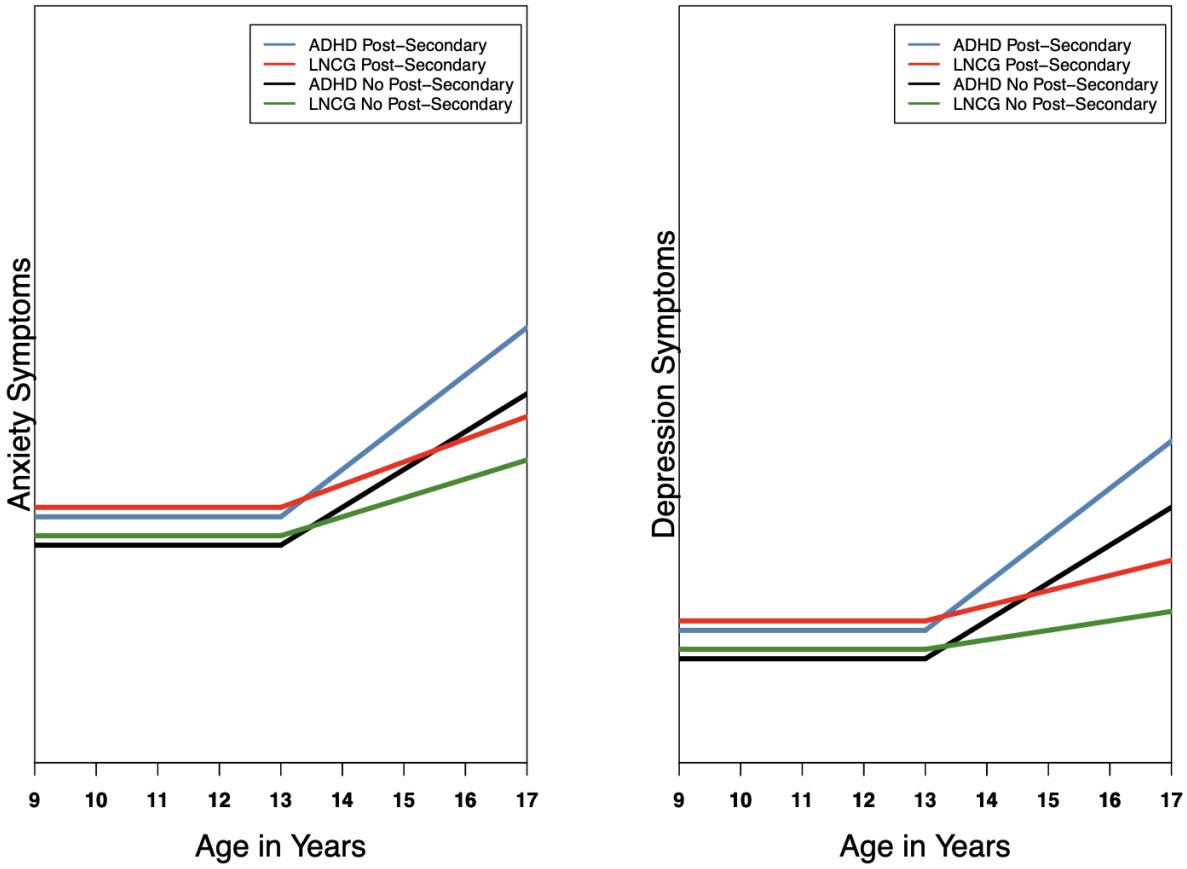
Hypothesis III. A third possibility was that the two post-secondary groups (i.e., ADHD Post-Secondary and LNCG Post-Secondary) would have higher levels of anxiety and depression than the non-post-secondary groups (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary). Some of the literature suggests that anxiety is not uncommon among gifted children and adolescents (Guignard et al., 2012) and that high-achieving high school students enrolled in advanced placement courses or international baccalaureate programs report high levels of stress and depression (Suldo et al., 2018). Similarly, university undergraduate students, medical students, law students, and graduate students report higher levels of anxiety and depression than the general population (Dammeyer & Nunez, 1999; Dyrbye et al., 2006; Eisenberg et al., 2009; Evans et al., 2018; Rotenstein et al., 2016). On this view, I would expect higher levels of anxiety and depression in the post-secondary groups than the non-post-secondary groups, especially in the later adolescent years when students are competing for placement in post-secondary programs.

With respect to slopes, I expected the post-secondary groups to experience greater increases in anxiety and depression from ages 13-17 than the non-post-secondary groups because of the stress and pressure to succeed academically and enrol in post-secondary education. Many studies have indicated that high achieving post-secondary students report higher levels of anxiety and depression than the general population (e.g., Barker et al., 2018; Cooke et al., 2006; Ibrahim et al., 2013; Twenge et al., 2010) and one study noted that even before they entered university, high-achieving high school students enrolled in advanced placement courses or international baccalaureate programs reported high levels of stress and depression (Suldo et al., 2018). Thus, increases in symptoms of

anxiety and depression in adolescence would be expected, particularly in the later years when students were preparing for the transition out of high school. See Figure 2.5 for hypothesized trajectories.

Figure 2.5

Hypothesized Trajectories (Hypothesis III) of Anxiety and Depression Symptoms from Ages 9 through 17



Machine Learning

The objective for Chapter 7 was to determine if machine learning could accurately predict adolescents with ADHD histories who would enrol in post-secondary studies based on ADHD symptoms, academic achievement, symptoms of internalizing disorders, and demographic characteristics. Recently, machine learning has been used in the ADHD literature to predict individuals who may or may not have ADHD (e.g., Duda et al., 2016; Silverstein et al., 2019; Tenev et al., 2014; Ustun et al., 2017; Yasumura et al., 2017). One of the benefits of machine learning is that a large amount of data can be considered at once, and the importance of each variable as a predictor of a class can be determined. In the present thesis, machine learning was selected because the trajectories alone cannot provide information about whether ADHD symptoms, academic achievement, symptoms of internalizing disorders, and certain demographic characteristics, together, can predict post-secondary enrolment for those with ADHD histories. Furthermore, the trajectories could not evaluate which factors are the best predictors of post-secondary enrolment. Although longitudinal data is both beneficial and necessary when considering the development of persons with ADHD histories, it is not always feasible to collect a large amount of data, such as that of the MTA. Thus, it was worth investigating if post-secondary enrolment could be predicted from demographic characteristics and measures that could easily be administered and obtained by a clinician during an ADHD diagnostic assessment.

Summary

A lifespan perspective on ADHD from childhood to adulthood is missing from the available research (Franke et al., 2018). This thesis aimed to further understanding of

how adolescents with ADHD histories who eventually attend post-secondary education differ from those with ADHD histories who do not attend post-secondary education. The LNCG served as a control group, allowing for the comparison of typical development for adolescents without ADHD who do or do not eventually attend post-secondary. This thesis examined ADHD histories from childhood to emerging adulthood to add to knowledge about the lifelong trajectories of ADHD.

Academic outcomes and internalizing disorders were selected because of their strong relations with both ADHD (e.g., Angold et al., 1999; Arnold et al., 2020; Erskine et al., 2016; Frazier et al., 2007; Loe & Feldman, 2007a; Schatz & Rostain, 2006; Tannock, 2009; The MTA Cooperative Group, 1999) and post-secondary achievement (e.g., Barker et al., 2018; Berger & Milem, 1999; Berkner & Cataldi, 2002; Berkner & Choy, 2008; Bjelland et al., 2008; Brown et al., 2008; Chang et al., 2006; Dammeyer & Nunez, 1999; Dyrbye et al., 2006; Eccles, 2005; Evans et al., 2018; Ibrahim et al., 2013; Marcenaro-Gutierrez et al., 2007; Parker et al., 2012, 2016; Porchea et al., 2010; Robbins et al., 2004, 2006; Rohde et al., 2013; Rotenstein et al., 2016; Suldo et al., 2018; Twenge et al., 2010). However, to my knowledge, factors related to post-secondary enrolment for adolescents with ADHD histories had not been studied, especially from a developmental viewpoint.

CHAPTER 3: METHOD AND ANALYSIS PLAN

The Multimodal Treatment Study of Children with Attention-Deficit/Hyperactivity Disorder

Background

Data from the MTA were used in this thesis. The MTA is a longitudinal study funded by the National Institute of Mental Health. The study began in 1994 as a multisite, multimodal treatment study of children with ADHD (Richters et al., 1995). The MTA was the first major clinical trial to focus on a childhood mental disorder. More specifically, the study was interested in determining whether combined medication and behavioural therapy had added benefits that exceeded medication alone. In general, they asked three questions: i) How do long-term medication and behavioural treatments compare with one another? ii) Are there additional benefits when they are used together? iii) What is the effectiveness of systematic, carefully delivered treatments versus routine community care? (MTA Cooperative Group, 1999a).

There were four gates leading to eventual enrolment in the study. First, a diagnosis of the combined type of ADHD (ADHD-C), according to the DSM–IV guidelines, had to be confirmed. To qualify for ADHD-C, children must have at least six symptoms from each of the inattentive and hyperactive-impulsive symptom categories. Second, children in the same classroom as a child already enrolled in the MTA were ineligible. Third, unlike many previous studies, there were no exclusions for comorbidity unless the comorbid disorder required treatment incompatible with the MTA treatment (e.g., psychosis, severe learning disorder (IQ < 80), major neurological or medical illness). Fourth, families who were deemed high-risk for drop-out (e.g., non-English-

speaking primary caregiver, family history of abuse, parent stimulant abuse) were ineligible for participation (Arnold et al., 1997a).

In 1992, six sites were chosen to participate in the MTA. From the six sites, 579 children between the ages of 7 and 9.9 were randomly assigned to one of four treatment conditions: systematic medication management, multicomponent behavioural treatment, combined behaviour and medication treatments, and community care referral (Arnold et al., 1997b). Participants in the first three groups received treatments for 14 months whereas the community treatment group was assessed and referred to appropriate resources in the community. At baseline (3 months), mid-treatment (~9 months), treatment endpoint (14 months), and 24 months (10 months follow-up), children and their parents, teachers, and peers completed comprehensive assessment batteries. Principal components analyses led to the identification of six major outcome domains: ADHD symptoms, oppositional/aggressive symptoms, social skills, internalizing symptoms, parent-child relations, and academic achievement (MTA Cooperative Group, 1999a).

At the end of the 24 months (10-month follow-up) a local normative comparison group (LNCG) of 289 children was recruited. These children were randomly sampled from the same schools and grades as the MTA children and were matched for age and sex. The same exclusion criteria, with the exception of a diagnosis of ADHD, applied to the LNCG as the MTA children. Of the 289 children, 31 children were diagnosed with ADHD at the time of recruitment; these children were followed but are often excluded from analyses. Both the MTA children and LNCG were followed from the 24 months (hence forth referred to as 2-year) through 16-year assessments. Assessments occurred at 2, 3, 6, 8, 10, 12, 14, and 16 years after treatment. From the original sample, 806

participants (*n* = 548 MTA, *n* = 258 LNCG) contributed to one or more data points between the 2- and 16-year assessments (Howard et al., 2016). Retention rates for the study are reported in Swanson et al. (2017). See Table 3.1.

Table 3.1

Adaptation of Table 2a from Swanson et al. (2017) Reporting Retention of MTA Sample

	Baseline 0	Childhood: 14 mos – Year 3	Adolescence: Year 6 – Year 8	Adulthood: Year 12 – Year 16
ADHD	*n* = 579	*n* = 515	*n* = 498	*n* = 476
LNCG	--	*n* = 258	*n* = 249	*n* = 241

Note. In childhood 289 LNCG were recruited but 31 were diagnosed with ADHD and removed from subsequent retention counts.

Treatments

Medication management began with a 28-day, double-blind, daily-switch titration of methylphenidate (i.e., Ritalin). Five randomly ordered repeats were used: 5mg, 10mg, 15mg, 20mg, or placebo. Doses were given at breakfast and lunch. Using teacher and parent ratings of response to each of the four doses, clinicians decided on the best dose for the child. The blind was broken and the agreed upon dose was set as the child's initial maintenance dose. Alternate medications were tried for children who did not respond adequately to the methylphenidate. Of the 289 children in the medication management and combined treatment, 256 successfully completed titration with an average initial dose of 30.5mg/day. By the end of the study, 212 participants were being successfully maintained on methylphenidate (MTA Cooperative Group, 1999a).

Throughout the school year, parent training, child-focused treatment and school-based interventions were included in the behavioural treatment. The parent training consisted of 27 group sessions and eight individual sessions. Sessions at the beginning were weekly and then tapered. School-based interventions consisted of 10-16 sessions of biweekly teacher consultation. Sessions focused on classroom behaviour management strategies. In addition, part-time behaviourally trained paraprofessional aides worked directly with the child for 12 weeks. The child-focused treatment consisted of an eight-week summer treatment program. Children attended the program nine hours/day for five days/week. Interventions included a point system tied to specific rewards, time outs, modelling, social reinforcement, group problem-solving, social skills training, and sports skills (MTA Cooperative Group, 1999a).

Community care participants did not receive either the medication or behavioural treatments. However, parents were given a report summarizing their initial study assessments and a list of mental health resources available in their community. At each wave, treatments they were receiving in the community were documented. During the 14-month treatment period, 67.4% of community care participants were taking ADHD medications prescribed by their own providers (MTA Cooperative Group, 1999a). Although many children in the community care referral were receiving medication, the quality and intensity of the treatment was inferior to the medication management provided by the MTA. In the medication management group, physicians closely worked with the parents and child regularly, carefully monitored for side effects, consulted with teachers on a monthly basis, and tended to deliver a higher dose of medication than the community care physicians.

Participants in all four treatment groups experienced a reduction in ADHD symptoms over time. Participants in the combined treatment and medication management showed significantly greater improvement than the behavioural strategy and community care referral. With respect to ADHD symptoms, there were no significant differences in the combined versus medication management. However, the combined treatment was superior for internalizing symptoms, and oppositional/aggressive symptoms. Additionally, parent-child relations, teacher-rated social skills, and reading achievement were superior in the combined treatment.

Generalizability and Limitations

As discussed above, the treatments provided by the MTA were superior to the treatments children would obtain from community care referral. The physicians in the study worked regularly and closely with parents, teachers, and the children. Additionally, the behavioural treatments provided were far more extensive than the psychological treatments a child would typically receive for ADHD. For example, the children were sent to an intensive summer treatment for eight weeks where they participated in nine hours of therapeutic activities per day. In contrast, typically children who receive psychological treatment for ADHD, in general, meet with a school psychologist or counsellor for an hour per week for a session.

Despite the intensive treatment, it is important to note that the treatment trial only lasted 14 months. After 14 months, depending on the child's personal situation, some children continued treatment, some changed treatment, and some discontinued treatment. Thus, beyond 14 months the treatment was not controlled. Therefore, accurate conclusions about the effectiveness of treatment cannot be drawn beyond 14 months.

Similarly, accurate conclusions about how treatment improves long-term functioning cannot be drawn (National Institute of Mental Health, 2009).

Children in the MTA began treatment in the mid 1990s. Thus, the medication they received at the time was immediate release methylphenidate. Presently, extended-release formulations of stimulant medications as well as some non-stimulant medications have become widely available. These extended release medications only require a once-a-day dose, in comparison to methylphenidate which required morning and afternoon administrations (National Institute of Mental Health, 2009). Nonetheless, methylphenidate is still used to treat ADHD and the conclusions from the MTA still point to the effectiveness of treating ADHD with medication.

Overall, no study is without limitations and over time medical treatments evolve as knowledge of diseases and disorders improves and new drugs are created. Nonetheless, the MTA was a carefully designed, thorough, longitudinal study that provided lasting contributions to the ADHD literature. As such, the data are still relevant today and continue to be used in publications that provide further insights into the long-term outcomes for persons with ADHD histories.

Publications with MTA Data

To date, there are over 140 publications that have used the MTA data. Although the study's main goal was to compare medication treatment to behavioural treatment, the publications with this data have covered an array of topics. For example, beyond considering types of treatments and long-term outcomes for persons with ADHD histories, the data have been used to discuss parent factors related to ADHD, such as parent aggression, maternal depression, parent-child relationships; peer relationships and

classroom behaviours; academic achievement; neuropsychological functioning; substance abuse; and predictors of adult outcomes. Nonetheless, there is still more to be explored given the complexity of ADHD and the extensiveness of the data collected by the MTA. Thus, in the present thesis I use the MTA data to explore a topic that has not previously been thoroughly explored in the MTA publications: ADHD and post-secondary enrolment. Although there have been studies with the MTA data that have examined college attendance (e.g., Howard et al., 2016), this thesis is unique as it explores how affect and academic achievement develop over time for adolescents who do and do not attend post-secondary studies. Given the importance of obtaining post-secondary education in today's world and the prevalence of ADHD in both children and adolescents, this is a relevant topic that needs further exploration.

The Present Research

Participants

Participants were selected from the MTA data. Children with ADHD-C (n = 579) were recruited between the ages of 7 to 9.9 years and were randomly assigned to one of four treatment groups: systematic medication management, multicomponent behavioural treatment, combined behaviour and medication treatments, and community care referral. Baseline assessments occurred at time of recruitment and again at 3, 9, and 14 months. At 14 months the study-provided treatment phase ended. From here, assessments occurred at 2, 3, 6, 8, 10, 12, 14, and 16-year follow-ups. At the 2-year follow-up, the local normative comparison group (LNCG; n = 289) were recruited. Thirty-one participants in the LNCG were identified as having ADHD and were subsequently removed from the data set (n = 258).

In this thesis, I use MTA data from Years 2 through 10 for participants under 18 years of age. I have chosen to begin analyses at Year 2 because at this time the LNCG was recruited; prior to Year 2 there is no comparison group. With the exception of school performance, the time points cover ages 8 through 18. For school performance, the time points cover Grades 4 through 12. Additionally, all children had to be classified as post-secondary or non-post-secondary (see Measures for details). Thus, of the potential 837 participants from the MTA, 770 were included in the present study (n = 250 LNCG).

Of the 770 participants, 79.4% were boys (n = 611). At baseline, the mean age for the participants with ADHD histories was 8.5 years. With respect to original treatment groups, of the 520 children with ADHD, 24.8% were in the systematic medication management treatment group, 25.4% were in the multicomponent behavioural treatment group, 26.0% were in the combined behaviour and medication treatments, and 23.8% were in the community care referral group. The mean age of biological mothers at the time of the participant's birth was 27.60 and 29.22 for children with ADHD and the LNCG, respectively. At Year 2 (baseline for the LNCG), the mean age for the LNCG was 10.4 years. In line with previous MTA studies, participant ethnicity was recoded into four groups: Caucasian (62.9%), Black (17.3%), Hispanic (9.5%), and Other (10.4%). Additionally, annual household income was coded as low (< $10,000; 7.3%) versus not low. Finally, participants were classified as advantaged (vs. disadvantaged) if their parents were married/cohabitating and at least one parent had a college degree (41.3%).

Measures

Hundreds of measures were included in the baseline and follow-up assessments for the MTA. Here, I describe only the measures used for analyses in the present research.

ADHD Symptoms

ADHD symptoms were measured using the Swanson, Nolan and Pelham Questionnaire (SNAP-IV; Swanson et al., 2001). Items 1-9 correspond to symptoms of inattention and items 11-19 correspond to symptoms of hyperactivity/impulsivity outlined in the DSM-IV. Symptoms are rated on a scale from 0 (not at all) to 3 (very much). The parent version of the SNAP was completed at baseline, 14 months, and 2, 3, 6, 8, and 10-year follow-up time points. The teacher version of the SNAP was completed at baseline, 14 months, and 2, 3, 6, 8, 10, 12, and 14-year follow-up time points.

In the present study a composite score was created to combine parent and teacher ratings of inattentive and hyperactive/impulsive ADHD symptoms, following procedures recommended by Kraemer, and documented in Howard et al. (2015). First, the baseline means and standard deviations were calculated for both parents and teachers for symptoms of inattention and hyperactivity/impulsivity. Note, at baseline the LNCG had not yet been recruited so they do not have baseline SNAP scores. Additionally, standardized scores at baseline were computed ($M = 0$, $SD = 1$). Next, scores at subsequent waves (i.e., Year 2 through Year 10) were centered around the respective raw baseline means and standard deviations for parent and teacher scores. Scores for the LNCG were manually standardized relative to the ADHD baseline sample means and standard deviations. Finally, rescaled parent and teacher scores within each wave were

averaged to create composite parent-teacher ratings of both inattentive and hyperactive/impulsive symptoms.

Academic Achievement

Standardized academic achievement was measured with the Wechsler Individual Achievement Test (WIAT; Psychological Corp, 1992). The WIAT can be administered to children between the ages of 5 years 0 months to 19 years 11 months. The WIAT consists of eight subtests, which are summarized to yield composite scores for reading, language, writing, and mathematics. The eight subtests include:

i) mathematics reasoning (50 items) – student responds to a variety of math concepts items using speaking, pointing, or writing

ii) spelling (50 items) – student writes words dictated by the examiner

iii) reading comprehension (38 items) – student reads short passages and provides oral responses to comprehension questions

iv) numerical operations (40 items) – student performs basic operations (i.e., addition, subtraction, multiplication, division)

v) listening comprehension (36 items) – examiner reads passages and student orally responds to comprehension questions

vi) oral expression (40 items) – student is required to orally describe scenes, explain steps involved in completing a process, and provide directions

vii) written expression – student is given 15 minutes to write a passage about a given topic; only administered in Grades 3 through 12.

Each subtest can be administered in 30-60 minutes. The standardized mean score for the inventory and for each subtest is 100 with a standard deviation of 15. The basic reading,

mathematical reasoning, and spelling subtests can be used together as a screening measure (i.e., the WIAT Screener). In the MTA, the full WIAT was administered at baseline and the WIAT Screener was completed at baseline, 14 months and all follow-up time points (i.e., 2, 3, 6, 8, 10, 12, 14, 16 years). Thus, in the present study, the WIAT screener is used to measure academic achievement.

School Performance

At each time point, parents of the children in the MTA were asked to provide information about their child's performance in school (i.e., report card data). These reports were used to determine school performance outcomes in the present study. Specifically, overall GPA and grades in subjects that align with the standardized subscales of the WIAT Screener (i.e., mathematics and English) were used as measures of school performance from Grades 4 through 12. Mathematics and English grades were rated on a five-point scale, with a grade of "A" being coded as "5" and a grade of "F" being coded as "1". Grade point average was on the traditional four-point scale. Because parents could provide report cards from all years between follow-ups, the school performance data is not aligned with the follow-up waves. Thus, rather than organizing by child age, the models of school performance are organized by grade and the number of participants in each grade do not match the number of participants in each follow-up wave.

Anxiety Symptoms

Anxiety symptoms were measured using the Multidimensional Anxiety Scale for Children (MASC; March, 1998). The MASC is a normed self-report questionnaire used to assess anxiety in children and adolescents (i.e., ages 8-18 years). Participants are asked

to rate their own behaviour on a 4-point scale (1 = never true about me, 2 = rarely true about me, 3 = sometimes true about me, 4 = often true about me). The 39-items are used to assess physical symptoms of anxiety, harm avoidance, social anxiety, and separation/panic anxiety. The MASC features a scale that measures total anxiety and two additional indexes for anxiety disorder and inconsistency. The MASC was completed (by participants under 18 years of age) at baseline, 9 months, 14 months, and 2, 3, 6, 8, and 10 years. After the 10-year follow-up, all participants were at least 18 years of age, so the MASC inventory was no longer appropriate. Scoring represents the mean score for all 45 items, with a possible range from 1 to 4.

Depression Symptoms

Depression symptoms were measured using the Children's Depression Inventory (CDI; Kovacs, 1992). The CDI is a self-report questionnaire used to assess depression in children and adolescents (i.e., 6-17 years). Participants are presented with three alternative statements (e.g., "I am sad once in a while", "I am sad many times", and "I am sad all the time") each designed to evaluate a symptom of depression (e.g., sadness, guilt, loss of interest, fatigue); responses are scored from 0 to 2. The 27-item measure is used to measure cognitive, affective, and behavioural indicators of depression. The items can be divided into five subscales: anhedonia, negative self-esteem, ineffectiveness, interpersonal problems, and negative mood. The CDI was completed (by participants under 18 years of age) at baseline, 9 months, 14 months, and 2, 3, 6, 8, and 10 years. After the 10-year follow-up, all participants were at least 18 years of age, so the CDI inventory was no longer appropriate. Scoring represents the mean score for all 27 items, with a possible range from 0 to 2.

Post-Secondary Enrolment

To determine if participants eventually enrolled in post-secondary studies, items from two demographic inventories and a school history inventory were assessed. The first demographic inventory contained data from the Year 6 to Year 10 follow-up for 747 participants. From this inventory, current grade in school and last grade completed were used to identify participants currently enrolled in college. Additionally, two variables were used to identify participants who had completed a post-secondary program. The second demographic inventory contained data from the Year 12 to Year 16 follow-up for 740 participants. Four variables were used to identify students currently enrolled in a post-secondary program (excluding vocational programs), either full-time or part-time. Finally, the school history inventory consisted of data from the Year 12 to Year 16 follow-up for 740 participants. Four variables were used from the school history inventory to determine if participants had completed a post-secondary program (i.e., associate degree, bachelor's degree, post-college degree). Using these three data sets, and removing participants in the LNCG identified as having ADHD, 770 participants were identified as either having enrolled in post-secondary education during their time in the MTA or not having enrolled. These 770 participants had a range of post-secondary education experiences, including direct entry after high school and delayed entry. Furthermore, not everyone who enrolled eventually completed their post-secondary studies. The remaining 98 participants either could not be classified (n = 67) or were members of the LNCG who were diagnosed with ADHD (n = 31) and thus were excluded from the analyses. The 770 participants were classified as follows: ADHD Post-

Secondary (*n* = 332), ADHD No Post-Secondary (*n* = 188), LNCG Post-Secondary (*n* = 205), and LNCG No Post-Secondary (*n* = 45).

Baseline Covariates and their Descriptive Statistics

In line with previous MTA publications and feedback from the MTA Cooperation, relevant covariates from the demographic questionnaires were chosen as control variables. More specifically, all model analyses control for sex, study site, ethnicity, low-income status, age of biological mother, parent education/two-parent household (advantaged = parents married/cohabitating and at least one parent is university educated, disadvantaged = parents are not together and neither parent has a university education), and diagnosis of externalizing disorder (i.e., oppositional defiant disorder or conduct disorder). Additionally, for participants with ADHD histories, three contrast treatment codes were calculated and entered as covariates. More specifically, treatment groups were separated based on whether the treatment consisted of medication (i.e., MTA medication algorithm effect), medication and psychotherapy versus medication alone (i.e., multimodal superiority effect), and behavioural therapy versus community referral (i.e., behavioural substitution effect). See Table 3.2 for details on scoring and Table 3.3 for descriptive statistics.

Table 3.2

Coding Used to Determine Contrast Treatment Codes

Original Treatment	Categorical Variable Codes		
	Medication	Multimodal	Behavioural
Medication Strategy	0.5	-1	0
Behavioural Strategy	-0.5	0	1
Combined Strategy	0.5	1	0
Community Strategy	-0.5	0	-1

Table 3.3

Descriptive Statistics for Time-Invariant Covariates for the Four Groups

	ADHD Post-Secondary (n = 332)	ADHD No Post-Secondary (n = 188)	LNCG Post-Secondary (n = 205)	LNCG No Post-Secondary (n = 45)
Sex (% male)	75.0	86.7	79.5	80.0
Study Site (% at each site)				
Site 1	14.8	19.1	16.6	17.8
Site 2	15.1	15.6	17.1	8.9
Site 3	13.6	19.7	13.7	31.1
Site 4	22.6	11.7	19.0	15.6
Site 5	20.8	12.8	17.1	8.9
Site 6	13.3	20.7	16.6	6.7
Ethnicity (%)				
White	56.4	64.5	69.8	46.7
Black	21.3	19.6	8.3	24.4
Hispanic	12.2	5.1	11.2	22.2
Other	10.1	10.8	10.7	6.7
Income Status (% low)	6.6	12.8	2.0	13.3
Age of Mother (years)	28.6	25.8	29.9	25.9
Parents (% advantaged)	48.2	20.7	54.6	15.6
Externalizing Disorder (%)	28.2	42.7	7.3	20.0
Treatment Groups				
Medication Strategy (%)	25.0	24.5	--	--
Behavioural Strategy (%)	25.9	24.5	--	--
Combined Strategy (%)	26.5	25.0	--	--
Community Strategy (%)	22.6	26.1	--	--

Missing Data

Data from the 2-, 3-, 6-, 8-, and 10-year follow-ups were used. Of the 770 participants, 558 (72.5%) had complete data across all waves; 749 participants had at least 1 wave of data. See Table 3.4 for a summary of missing data.

Table 3.4

Number of Participants Missing Data

	Number of Missing Waves					
	0	1	2	3	4	5
ADHD	354	61	47	20	17	21
LNCG	204	26	14	3	3	0
Total	**558**	**87**	**61**	**23**	**20**	**21**

Note. 0 = no missing data, 5 = missing data at all waves

Two missing data analyses were conducted. Analyses compared variables for adolescents with ADHD histories and the LNCG, separately. For both missing data analyses, the following variables were considered: age at baseline, grade at baseline, household income, birthweight (pounds), age of biological mother at child's birth, sex, ethnicity (coded White, Black, Hispanic, Other), parents' marital status (coded married/cohabitating vs. not), low-income status (coded annual household income < $10,000 vs. not), income from public assistance (e.g., welfare, social security income), mother education, father education, hospitalizations of the child, speech problems, number of school absences, school expulsions or suspensions, repeated school grade, parent mental health history, child's physical health (coded as good vs. not), and original

treatment assignment (medication management, multimodal treatment, behavioural substitution).

In the first analysis, the variables were analyzed using *t*-tests and χ^2-tests to determine if there were differences in those who could be classified based on post-secondary status (n = 770) and those who could not be classified (n = 67). Within the ADHD histories group, ethnicity (p = .01) and mother education (p = .007) differed between those who could and could not be classified. Participants who could not be classified were more often Hispanic and had mothers with lower education. In the LNCG, biological mother's age at time of child's birth (p = .001), ethnicity (p = .04), mother education (p = .007), and father education (p = .02) differed between those who could and could not be classified. Participants who could not be classified were more often Black, had younger mothers, mothers with lower education, and fathers with lower education.

In the second analysis, the same variables were analyzed using *t*-tests and χ^2-tests to determine if there were differences in those who had complete (n = 558) versus incomplete data (n = 212). Within the ADHD histories group, biological mother's age at time of child's birth (p < .001), low-income status (p = .02), and income from social assistance (p = .03) differed between those with complete versus incomplete data. Participants who had incomplete data were more likely to have younger mothers, low-income status, and receive income from social assistance. In the LNCG, biological mother's age at time of child's birth (p = .02) differed between those with complete versus incomplete data. Participants with incomplete data were more likely to have younger mothers. Overall, there were minimal differences between participants who

could and could not be classified according to their post-secondary status and there were minimal differences between participants with complete versus incomplete data. It is unlikely that the data has biases due to attrition or classification, however, to be confident that the data are missing at random the variables that were found to significantly differ between groups were added to all latent curve modelling analyses if they were not one of the covariates specified in Chapter 3. For all latent curve modelling analyses, full information maximum likelihood estimation (FIML) was used. With FIML, all participants who have completed at least one wave of data are included in the model; missing values are not replaced, but rather model parameters are estimated based on all available information in the variance-covariance matrix. Under the missing at random assumption, unbiased parameter estimates can be obtained with FIML for longitudinal analyses even with a high level of missing data (Enders, 2010).

Data Analysis Plan

Latent Curve Modelling

In the present research, the MTA data are analyzed using latent curve modelling, a type of structural equation modelling (SEM). Latent curve model, or latent growth model, refers to a class of models for analyzing longitudinal data in structural equation models (Kline, 2005). With latent curve modelling, repeated measures of a construct are incorporated as multiple indicators of one or more underlying latent curve factors (Curran et al., 2014). Through latent curve modelling, we can use observed time-specific measures to make inferences about the existence of an underlying, continuous, unobserved latent growth process. One advantage of latent curve modelling is that it is

capable of capturing interindividual differences in intraindividual stability and change over time (Curran et al., 2014).

The growth factors in latent curve modelling are interpreted as individual differences in the growth trajectories of attributes over time (McArdle, 1988). The individual growth trajectories allow us to look at levels of attributes and rates of change in attributes over time. For straight line growth models, the level is modelled as the intercept and the rate of change is modelled as the slope (Duncan & Duncan, 2009). In addition to describing growth at both the group and individual level, latent curve modelling can be used to study predictors of individual differences in growth (Duncan & Duncan, 2009). Because latent curve modelling is a type of highly restricted SEM, it shares many of SEM's strengths, including "an ability to test the adequacy of the hypothesized growth form, to incorporate both fixed and time varying covariates, to correct for error in the observed indicators, to incorporate growth on several constructs simultaneously, and to develop from the data a common developmental trajectory, thus ruling out cohort effects" (Duncan & Duncan, 2009, p. 3).

A general rule-of-thumb is that only data sets that include three or more assessment points are suitable for latent curve modelling because they allow evaluations of the validity of the straight-line growth and trajectory model (Duncan & Duncan, 2009). Models typically consist of an intercept factor and slope factor. The intercept characterizes one point on the growth curve. The collection of slopes (one per person) characterize the unique shape of change for each individual (Duncan & Duncan, 2009).

The design of the MTA was such that not every participant had data for every age; each participant, on average, had four timepoints of data. Furthermore, there was a

lot of variability in age at each assessment, as each assessment was completed over several months. Rather than categorizing participants by wave of assessment, they were categorized by age because of the heterogeneity within each wave. However, there were several ages for which each participant did not have data because the follow-ups were approximately every two years. When moving from wave of assessment to chronological age one option is to treat the ages for which there is no available data as missing data (Bollen & Curran, 2006). In doing so, the wave of assessment is ignored in the estimation of the model. A latent curve model is then fit to the partially missing restructured data using common missing data procedures, such as maximum likelihood or multiple imputation.

In summary, my thesis used data collected through a repeated measures design, following individuals from childhood through adulthood. The thesis design permitted modelling of developmental trajectories, obtained through latent curve modelling. Latent curve modelling is a useful analysis for this type of longitudinal data because it can provide insights into if and when groups differ and how each group may change over time.

Model Testing. In a typical latent curve model, it is assumed that the data of the individuals being analyzed represent a random sample of observation from a single population (Duncan & Duncan, 2004). This assumption implies that data from different individuals follow similar developmental processes. In contrast, with multi-group latent curve modelling, ordinary growth curve models are fitted in each sample (e.g., ADHD Post-Secondary, ADHD No-Post Secondary, LNCG Post-Secondary, LNCG No Post-Secondary) simultaneously for all groups. The original intention was to test for

differences between all four groups using multi-group latent curve modelling. However, the LNCG No Post-Secondary group had few participants (n = 45) in comparison to the other three groups. This small sample size led to substantial convergence issues when attempting to run a model that had a larger number of free parameters across the groups. Instead, grouping factors were entered into the model as predictors. More specifically, ADHD status (ADHD vs. LNCG), post-secondary status (post-secondary vs. no post-secondary) and the interaction between ADHD status and post-secondary status were included as predictors of both the intercept and slope. This approach is equivalent to multi-group analysis in which the predictor effects, growth factor variables, and residuals are identical in all four groups. A consequence of this approach is that it does not have the same flexibilities as multi-group modelling because, as with the single-group model, the covariates have been restricted to a single overall effect. Additionally, there were too few data points at ages 8 and 18 and in Grades 4 and 5 so these observations were excluded in all latent curve models. The total number of data points available for ages 8 and 18 and Grades 4 and 5 are reported in the descriptive tables for each latent curve model.

Across all latent curve models, model fit was evaluated using several fit indices. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are comparative fit indices. Values closer to 1 indicate good model fit, with values greater than .90 indicating acceptable model fit (Kline, 2005). The Root Mean Square Error of Approximation (RMSEA) is an absolute fit index scaled as a badness-of-fit statistic. Values less than .05 indicate good model fit, with values between .05 and .08 indicating acceptable fit (Hu & Bentler, 1999). The Standardized Root Mean Square Residual (SRMR) is also an

absolute fit index that is a badness-of-fit statistic. A value of 0 would indicate perfect fit, with values of less than .08 indicating acceptable fit. Chi-square statistics can also be used as a measure of fit, however, the chi-square value is sensitive to sample sizes. Thus, for all latent curve modelling analyses the Chi-square statistics are reported but are not typically used to evaluate model fit. All models were run using Mplus (Muthén & Muthén, 1998-2017).

Supervised Machine Learning

Machine learning is "programming computers to optimize a performance criterion using example data or past experience" (Alpaydin, 2010, n.p.). In the present study, I use machine learning to determine if a model can be trained to accurately predict post-secondary enrolment in adolescents with ADHD histories, using data from ages 14-17). There are many applications for machine learning, most of which involve data mining (Kotsiantis, 2007). Of particular interest to the proposed studies is classification within supervised machine learning.

With supervised machine learning, we are interested in learning to predict the class of a certain variable (Alpaydin, 2010). For example, perhaps we want to learn the class of an "adoptable dog". We could gather information on dogs previously adopted from shelters and label them; dogs who were adopted would be positive examples and dogs who were not adopted would be negative examples. With class learning, in an ideal situation we find a description that is shared by all positive examples and none of the negative examples. What attributes are shared among dogs that get adopted but not shared among dogs who are not adopted? Perhaps it turns out that dogs who get adopted are younger, friendlier, and healthier. These three attributes will serve as our inputs to the

class recognizer; other attributes will be considered irrelevant. Once the inputs have been selected, we can train our model to make predictions about which new dogs at a shelter will be adopted based on these attributes. Based on an analysis of the data, the model might decide that for a dog to get adopted, its age, friendliness, and overall health should be within a certain range. We can then see how accurate the model is based on the proportion of correct predictions. True positives would be cases where a dog was adopted, and the model correctly predicted the dog's adoption. True negatives would be cases where a dog was not adopted, and the model correctly predicted this outcome. We can also have false positives and false negatives where the model incorrectly predicts the dog's adoption status.

There are many different machine learning algorithms. Because I was interested in determining whether machine learning can accurately predict which adolescents with ADHD histories will attend post-secondary studies, I tested several algorithms. More specifically, I tested simple linear (i.e., Linear Discriminant Analysis), nonlinear (i.e., Classification and Regression Trees, *k*-Nearest Neighbors), and complex nonlinear (i.e., Support Vector Machine; Random Forests) machine learning algorithms. Across all of these methods, part of the sample is used for training the model and part is used for testing the model. The subset of data specified for training is marked as either positive or negative examples. After running the models, we can check the sensitivity, specificity, positive likelihood ratio, and negative likelihood ratio of the model. High sensitivity and specificity are indicative of a model that makes accurate predictions. We also want a high positive likelihood ratio and a low negative likelihood ratio. Using the dog adoption example from above, the positive likelihood ratio would be the probability of a true

positive (i.e., the dog was adopted and the model correctly predicted the dog was adopted) divided by the probability of a false positive (i.e., the dog was not adopted and the model incorrectly predicted that the dog was adopted). Similarly, a negative likelihood ratio would be the probability of a true negative divided by a false negative. Both ratios can be calculated with the equations outlined below (Yasumura et al., 2017). Additionally, we can evaluate the models based on their Kappa value. The Kappa value compares observed accuracy (i.e., percentage of correctly classified cases) with expected accuracy (i.e., random chance). Because it takes random chance into account, it is less misleading than observed accuracy alone.

$$sensitivity = \frac{true\ positive}{true\ positive + false\ negative} \times 100$$

$$specificity = \frac{true\ negative}{true\ negative + false\ positive} \times 100$$

$$positive\ likelihood\ ratio = \frac{sensitivity}{1 - specificity}$$

$$negative\ likelihood\ ratio = \frac{1 - sensitivity}{specificity}$$

$$kappa\ value = \frac{observed\ accuracy - expected\ accuracy}{1 - expected\ accuracy}$$

Linear Discriminant Analysis (LDA). Linear discriminant analysis is a machine learning algorithm that attempts to model differences among samples assigned to classified groups. With LDA, the goal is to maximize the between-group variance to within-group variance ratio. By maximizing this ratio, the samples within each group have the smallest possible scatter, meaning the groups are the most separated from one

another (Stanimirova et al., 2013). Similar to analysis of variance and regression analysis, LDA attempts to express a dependent variable as a function of other measurements, only with LDA the independent variables are continuous and the dependent variable, also known as the class label, is the dependent variable. Similar to principal component analysis or factor analysis which both try to identify linear combinations of variables that best explain the data, LDA tries to model the difference between classes of data (Martinez & Kak, 2001).

Classification and Regression Trees (CART). Classification and regression tree analysis is a machine learning algorithm that uses decision tree algorithms for classification and regression learning tasks (Mehta, 2019). Decision trees can be thought of as if/else statements. In the present research, CART is used for classification learning tasks. The trees have categorical or discrete outcome variables. With CART, input variables are used to form rules about when to split the data to obtain the best classification of the outcome variable. At each level, a point at which to split the data is calculated, forming a node and two branches. The procedure then moves on to each of the two branches separately and seeks a new point at which to split the data within that branch. "Gain" is used to determine whether splitting the data at this point improves the classification or not, and the best gain for each branch is used to decide where the node is placed. The procedure continues until splitting the data no longer increases the gain or until a pre-defined stopping point is reached. The purity of the classes present in each terminal node of the tree is used to measure how well the tree has performed.

***K*-Nearest Neighbors (*k*-NN).** *K*-nearest neighbors is a machine learning algorithm that, much like CART can be used for classification and regression analyses. In

the present research, it is used for classification to classify adolescents with ADHD histories as either “post-secondary” or “no post-secondary”. With *k*-NN, the assumption is that similar things will be in close proximity to one another; birds of a feather flock together (Harrison, 2018). The similarity of data points is captured by calculating the distance between points on a graph. The *k* refers to the chosen number of neighbors. For example, 1-NN would use the distance to the nearest neighbor to classify a data point, whereas 3-NN would use the distance of the nearest three neighbors to classify a data point (i.e., if two neighbors belong to Class A and one belongs to Class B, that data point will be classified as A). To select the optimal *k* value, the *k*-NN algorithm is run several times with different *k* values; the *k* value that reduces the number of errors encountered while maintaining the algorithm’s ability to accurately classify is selected (Harrison, 2018). The optimal value of *k* tends to range from 3-10.

Support Vector Machine (SVM). The SVM training algorithm is a non-probabilistic binary linear classifier, meaning the algorithm builds a model that assigns new examples to either the positive or negative category (Cortes & Vapnik, 1995). The objective of the SVM algorithm is to identify a hyperplane in *N*-dimensional space, where *N* is the number of features, that distinctly classifies the data points (Gandhi, 2018). Many possible hyperplanes exist that could distinctly classify the data points, but SVM looks for the hyperplane that has the maximum *margin*. The margin is the plane that provides the maximum distance between the data points of the two classes. When the margin is maximized, future data points can be classified with greater confidence. Because data sets are rarely linearly separable, Kernel Trick can be used to try and find a non-linear decision boundary. With Kernel Trick, transformations are applied using

existing features, resulting in new features. The new features created are they key for the algorithm to find the non-linear decision boundary. In this study, I use Radial Basis Function Kernel to transform and generate new features by measuring the distance between one data point's center to all other data points' centers (Chen, 2019).

Random Forests (RF). Random forests is a machine learning algorithm that, similar to CART, uses decision trees to classify data. With RF, a large number of individual decision trees operate as an ensemble (Yiu, 2019). Each decision tree in the random forest produces a class prediction; the class with the most votes becomes the model's prediction. Random forests draws upon the idea of "strength in numbers"; a large number of relatively uncorrelated trees operating together outperform individual trees. Because the trees are relatively uncorrelated, the trees protect one another from their individual errors; even though some trees may incorrectly classify, others will not, so as a group the trees will classify in the right direction. Through a process known as bagging, each tree can randomly sample, with replacement, from the data set which results in different trees (Yiu, 2019).

Machine Learning in ADHD Research. More recently, machine learning has been used in the ADHD literature to predict individuals who may or may not have ADHD based on self-reports of symptoms (Silverstein et al., 2019; Ustun et al., 2017), EEG and MRI data (Tenev et al., 2014; Yasumura et al., 2017), and by comparing diagnoses of ADHD to diagnoses of Autism Spectrum Disorder (Duda et al., 2016). Using machine learning, Ustun et al. were able to use two adult self-report measures of ADHD to find six items that accurately distinguished people with ADHD from people without ADHD in the general population. Using a short screening tool is advantageous

because it is easy to administer and can serve as a starting place for diagnosing for practitioners. The benefit of machine learning is that it permits an evaluation of the accuracy of a screening tool. To my knowledge, no one has used machine learning to see if post-secondary enrolment can be accurately predicted in the ADHD population. Thus, in the present research I trained five models to see if machine learning can be used to accurately predict post-secondary enrolment versus no enrolment in adolescents with ADHD histories.

CHAPTER 4: DEVELOPMENTAL TRAJECTORIES OF ADHD SYMPTOMS

In this chapter the results of the latent curve modelling analyses for ADHD symptoms are presented. The goal was to address the following question: Do the trajectories of ADHD symptoms differ for the four groups of adolescents, that is, those with or without ADHD histories who did or did not attend post-secondary education?

Inattentive Symptoms

Table 4.1 shows the number of participants and the means and standard deviations for inattentive symptoms from ages 8-18. Figure 4.1 shows box plots of inattentive symptoms at each age. Figure 4.2 shows both the individual and average inattentive symptoms score for each age, separated by group. In the table and both figures the scores are presented using the original SNAP metric, where scores in each of the four groups are centered around the mean of the parent and teacher rating scores at baseline. Based on Figures 4.1 and 4.2, the slopes appeared to change from ages 8-13 and 13-18, with a peak at age 13. Thus, in addition to a linear latent curve model, a piecewise latent curve model was tested with the knot at age 13 and model fit was compared.

Likelihood ratio tests were performed to determine the optimal form of change between the unconditional linear model and the unconditional piecewise model. A Chi-square difference test showed that the piecewise function was better than the linear function, $\chi^2(4) = 36.74$, $p < .001$. The final piecewise model, which included the covariates, had excellent fit, $\chi^2(190) = 223.85$, $p = .047$, SRMR = .044, CFI = .978, RMSEA = .016 [.002, .023]. See Table 4.2 for a summary of the unstandardized and standardized model results. See Figure 4.3 for the implied trajectories for the four groups.

Table 4.1

Means and Standard Deviations for Inattentive Symptoms at Each Age, Separated by Group

	Age (in Years)										
	8	9	10	11	12	13	14	15	16	17	18
ADHD Post-Secondary											
N	2	119	158	178	102	79	124	129	175	132	24
Mean	0.34	1.16	0.88	1.13	0.93	1.32	1.04	0.81	0.89	0.93	0.93
SD	0.31	0.99	0.93	0.98	0.98	0.96	1.03	1.02	1.06	1.06	1.27
ADHD No Post-Secondary											
N	2	57	98	98	49	50	59	61	91	71	9
Mean	0.38	1.06	1.25	1.22	1.46	1.67	1.32	1.33	1.27	1.16	1.55
SD	1.08	0.99	1.14	0.93	0.93	1.00	0.94	0.93	1.11	1.08	1.43
LNCG Post-Secondary											
N	21	68	121	99	73	66	70	96	93	101	3
Mean	-0.20	-0.34	-0.33	-0.47	-0.32	-0.22	-0.34	-0.18	-0.14	-0.36	0.23
SD	0.71	0.73	0.81	0.70	0.81	0.70	0.73	0.76	0.80	0.69	1.23
LNCG No Post-Secondary											
N	10	15	26	22	16	16	17	20	23	17	--
Mean	-0.07	-0.10	-0.14	0.04	0.17	0.60	0.13	0.44	0.20	0.38	--
SD	0.78	1.02	0.71	0.85	0.91	0.97	0.43	1.14	0.78	1.20	--

Figure 4.1

Box Plots and Scatterplots Showing Inattentive Symptoms by Age

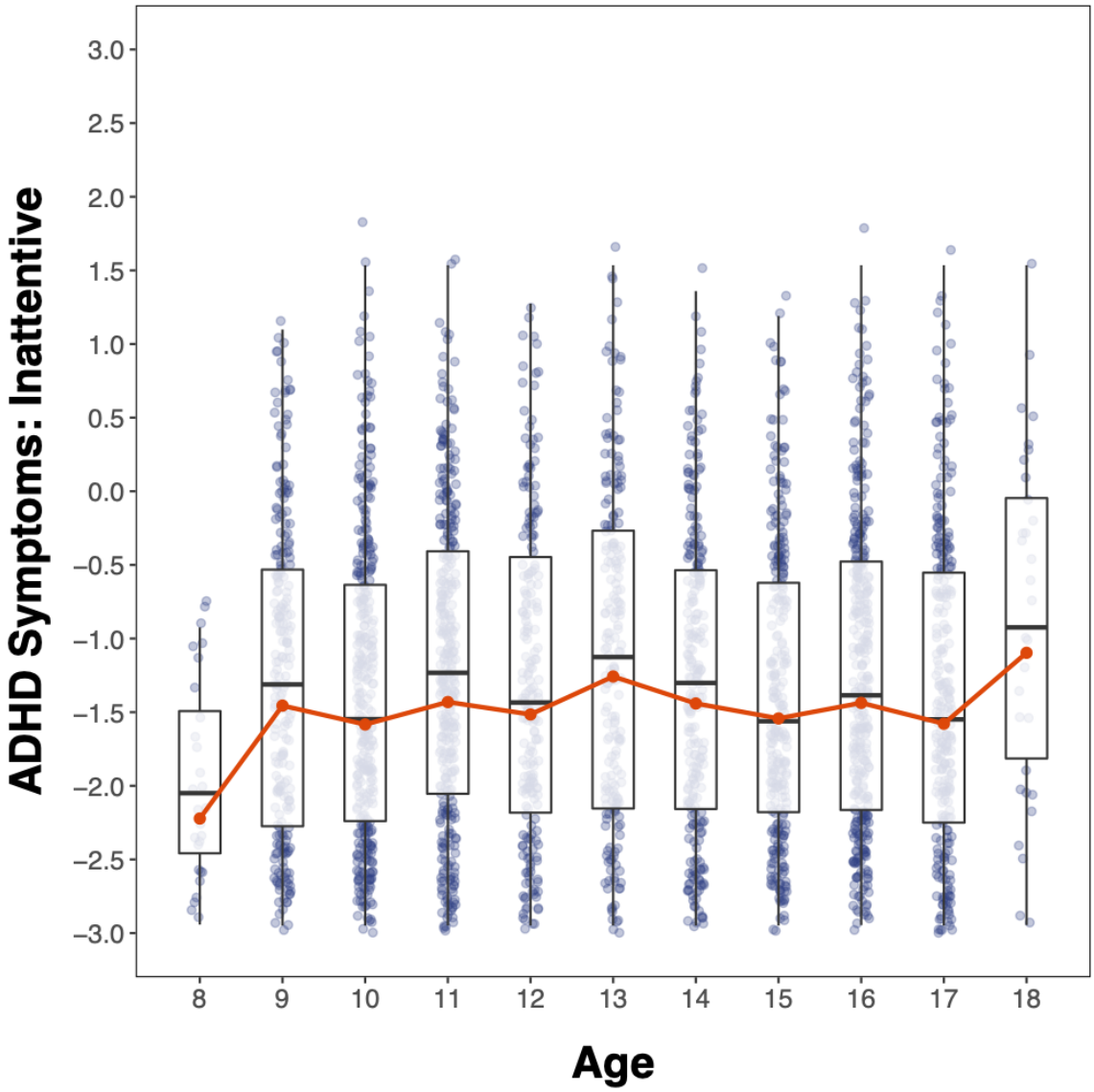


Figure 4.2

Individual and Mean Scores for Inattentive Symptoms by Age and Group

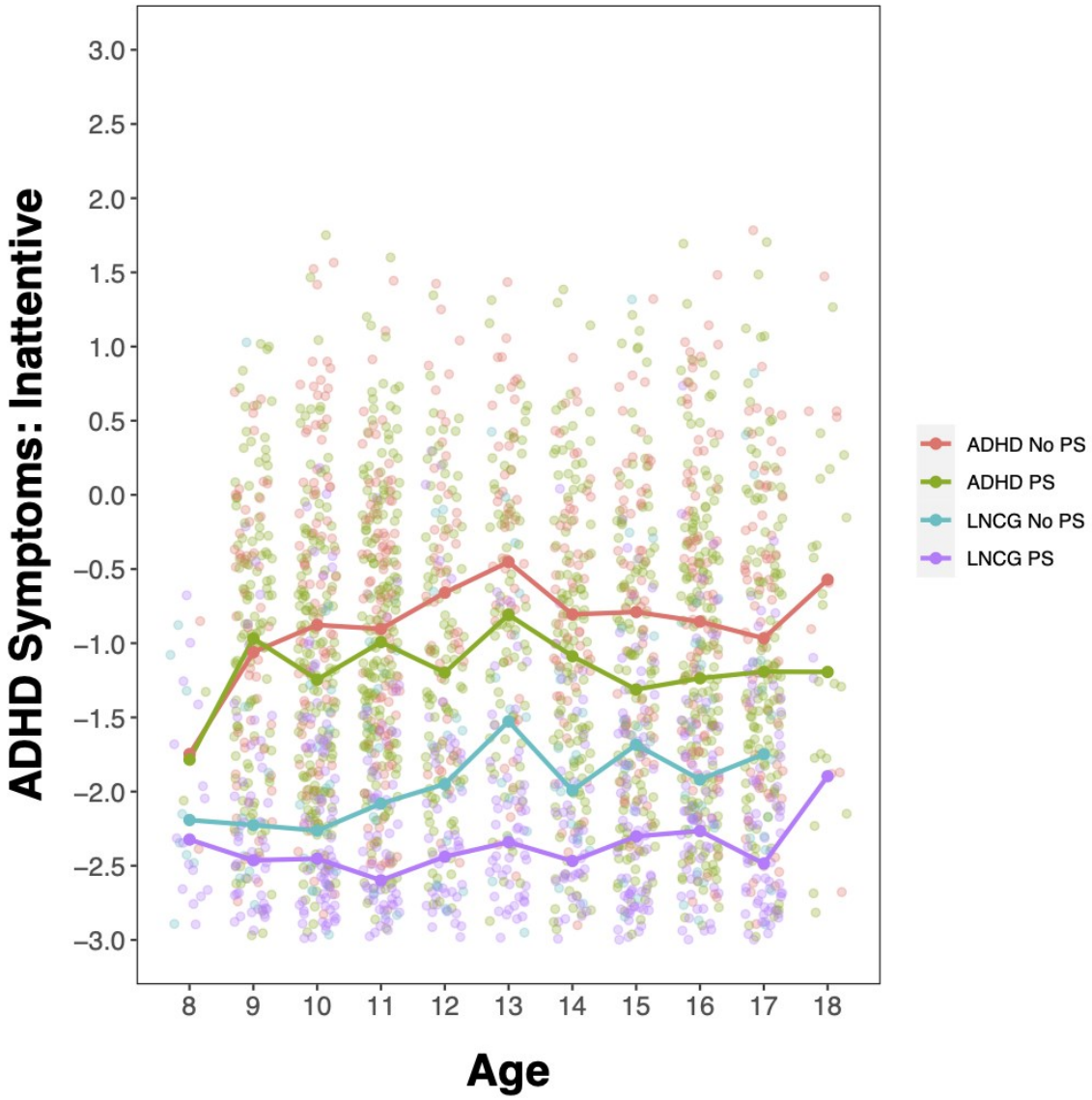


Table 4.2

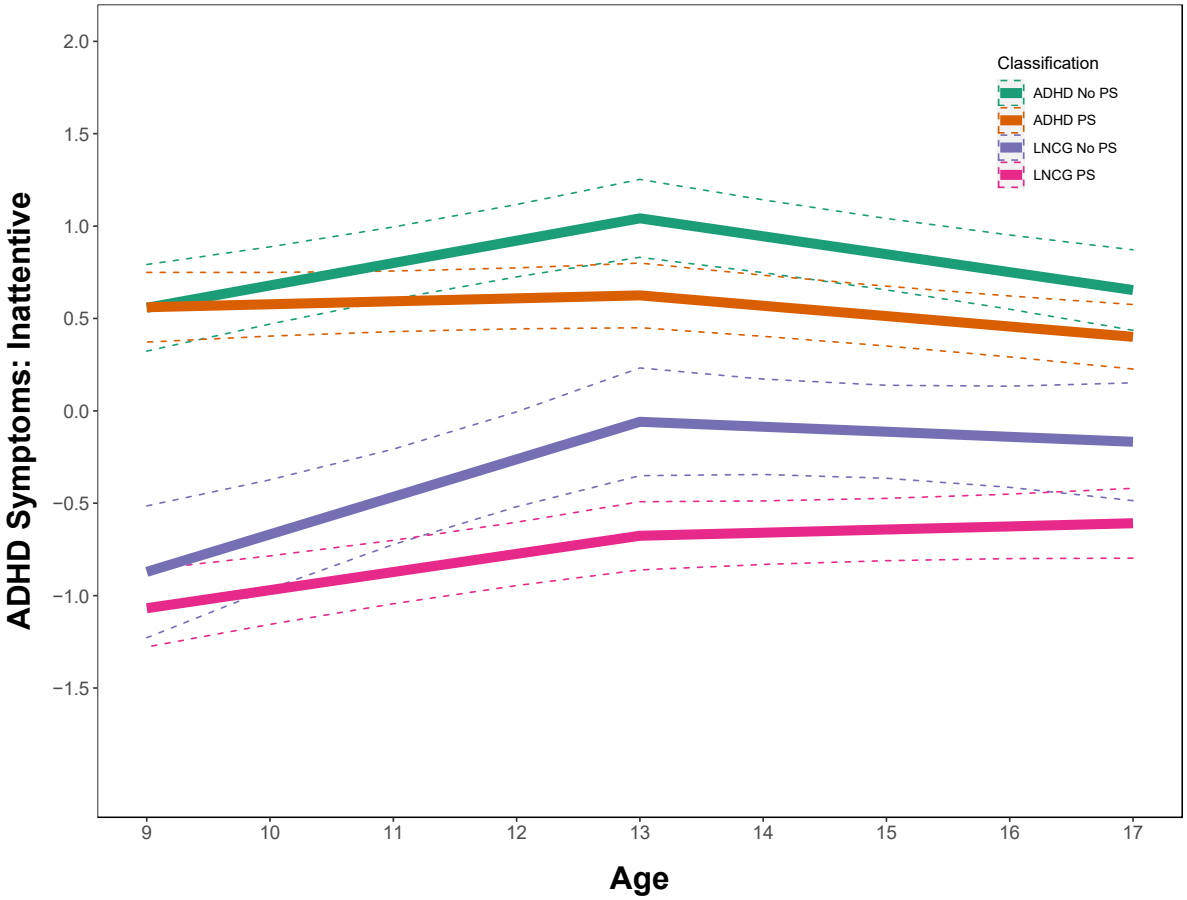
Inattentive Symptoms Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	-0.059	0.178	-0.058	0.176
ADHD	1.101*	0.173	0.516*	0.080
Post-Secondary	-0.617*	0.170	-0.278*	0.076
ADHD*Post-Secondary	0.200	0.196	0.098	0.096
Rate of Change (Slope Age 9-13)	0.203*	0.001	0.175*	0.146
ADHD	-0.082	0.069	-0.215	0.139
Post-Secondary	-0.105	0.067	-0.001	0.175
ADHD*Post-Secondary	0.000	0.078	0.914	0.280
Rate of Change (Slope Age 13-17)	-0.027	0.053	-0.176	0.346
ADHD	-0.070	0.060	-0.216	0.190
Post-Secondary	0.044	0.058	0.131	0.173
ADHD*Post-Secondary	-0.003	0.068	-0.009	0.220
Covariates				
Sex (Male)	0.275*	0.068	0.109*	0.027
Treatment Site 2	0.065	0.049	0.046	0.035
Treatment Site 3	0.021	0.037	0.023	0.040
Treatment Site 4	0.045	0.024	0.070	0.037
Treatment Site 5	0.003	0.019	0.006	0.036
Treatment Site 6	-0.001	0.016	-0.003	0.036
Ethnicity: Black	0.181*	0.086	0.066*	0.032
Ethnicity: Hispanic	-0.032	0.111	-0.009	0.033
Ethnicity: Other	0.033	0.095	0.010	0.028
Advantaged	0.087	0.061	0.042	0.030
Low-Income Status	-0.078	0.125	-0.020	0.032
Externalizing Disorder	0.242*	0.066	0.104*	0.029
Age of Mom at Birth	0.008	0.005	0.049	0.030
Social Assistance Income	0.025	0.090	0.009	0.032
Medication Management	-0.027	0.068	-0.011	0.027
Multimodal Superiority	-0.008	0.047	-0.005	0.027
Behavioural Substitution	0.024	0.048	0.013	0.027

*$p < .05$

Figure 4.3

Implied Trajectories for Inattentive Symptoms by Age and Group with 90% Confidence Bands



Overall, both ADHD histories and eventual post-secondary enrolment were associated with inattentive symptoms at age 13. At age 13, adolescents with ADHD histories had higher levels of inattentive symptoms than the LNCG. Similarly, at age 13, participants who did not eventually enrol in post-secondary studies had higher levels of inattentive symptoms than participants who eventually enrolled in post-secondary studies. Neither ADHD histories nor eventual post-secondary enrolment were significantly associated with the rate of change in inattentive symptoms, however, across all four groups there was a slight increase in symptoms from ages 9-13. Thus, there were mean-level group differences in inattentive symptoms, but the groups did not change differently over time.

The pattern in Figure 4.3 shows that, from ages 9-17, adolescents with ADHD histories had higher levels of inattentive symptoms than the LNCG. From ages 9-13, the trajectories for those who eventually enrolled in post-secondary studies were relatively flat (i.e., ADHD Post-Secondary and LNCG Post-Secondary). For those who did not eventually enrol in post-secondary studies, the symptoms increased slightly from ages 9-13 (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary). Although not statistically significant, this pattern suggests that in the early years, adolescents who do not eventually attend post-secondary studies may experience more severe inattentive symptoms and the symptom levels may increase over time. From ages 13-17, with the exception of the ADHD No Post-Secondary group, the trajectories were approximately flat – there was no significant change in symptoms for each of the groups during this time period. For the ADHD No Post-Secondary group there was a slight decline in symptoms from ages 13- 17. However, they continued to exhibit higher symptom levels than the

ADHD Post-Secondary group and LNCG. Again, however, the slopes were not significant in the model. Overall, both ADHD histories and post-secondary enrolment were associated with inattentive symptoms at age 13, but the rates of change from ages 9-17 across the four groups were not significantly different.

Hyperactive Symptoms

Table 4.3 shows the number of participants and the means and standard deviations for hyperactive symptoms from ages 8-18. Figure 4.4 shows box plots of hyperactive symptoms at each age. Figure 4.5 shows both the individual and average hyperactive symptoms score for each age, separated by group. In the table and both figures the scores are presented using the original SNAP metric. Based on Figures 4.4 and 4.5, the slopes appeared to change from ages 8-13 and 13-18, with a peak at age 13. Thus, in addition to a linear latent curve model, a piecewise latent curve model was tested with the knot at age 13 and model fit was compared.

Likelihood ratio tests were performed to determine the optimal form of change between the unconditional linear model and the unconditional piecewise model. A Chi-square difference test showed that the piecewise function was better than the linear function, $\chi^2(4) = 32.00$, $p < .001$. The final piecewise model, which included the covariates, had good fit, $\chi^2(190) = 309.72$, $p < .001$, SRMR = .051, CFI = .929, RMSEA = .029 [.023, .035]. See Table 4.4 for a summary of the unstandardized and standardized model results. See Figure 4.6 for the implied trajectories for the four groups.

Table 4.3

Means and Standard Deviations for Hyperactive Symptoms at Each Age, Separated by Group

	Age (in Years)										
	8	9	10	11	12	13	14	15	16	17	18
ADHD Post-Secondary											
N	2	119	158	178	102	79	124	129	175	132	24
Mean	-1.32	-1.18	-1.33	-1.33	-1.49	-1.38	-1.65	-1.79	-1.85	-1.83	-1.73
SD	0.38	0.90	0.88	0.82	0.83	0.95	0.84	0.88	0.84	0.91	0.95
ADHD No Post-Secondary											
N	2	57	98	98	49	50	59	61	91	71	9
Mean	-1.10	-1.20	-1.16	-1.20	-1.31	-1.03	-1.43	-1.46	-1.65	-1.84	-1.33
SD	1.15	0.97	1.00	0.97	0.97	0.98	0.84	0.90	0.86	0.84	1.26
LNCG Post-Secondary											
N	21	68	121	99	73	66	70	96	93	101	3
Mean	-2.32	-2.34	-2.41	-2.50	-2.41	-2.44	-2.55	-2.47	-2.60	-2.68	-2.14
SD	0.40	0.47	0.48	0.46	0.53	0.49	0.34	0.54	0.37	0.30	1.16
LNCG No Post-Secondary											
N	10	15	26	22	16	16	17	20	23	17	--
Mean	-2.25	-2.40	-2.25	-2.19	-2.22	-2.14	-2.22	-2.49	-2.23	-2.59	--
SD	0.60	0.30	0.51	0.66	0.65	0.77	0.55	0.25	0.64	0.35	--

Figure 4.4

Box Plots and Scatterplots Showing Hyperactive Symptoms by Age

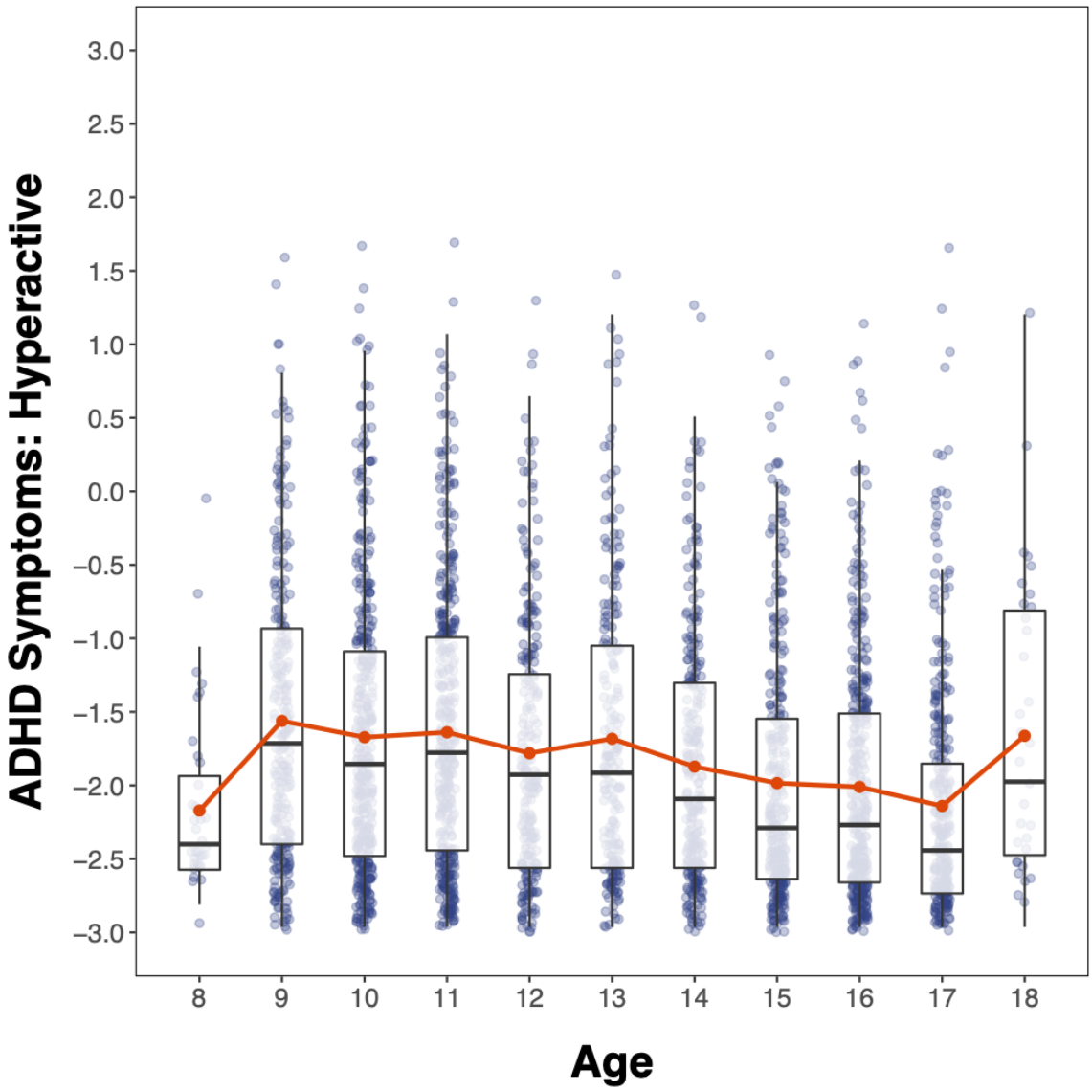


Figure 4.5

Individual and Mean Scores for Hyperactive Symptoms by Age and Group

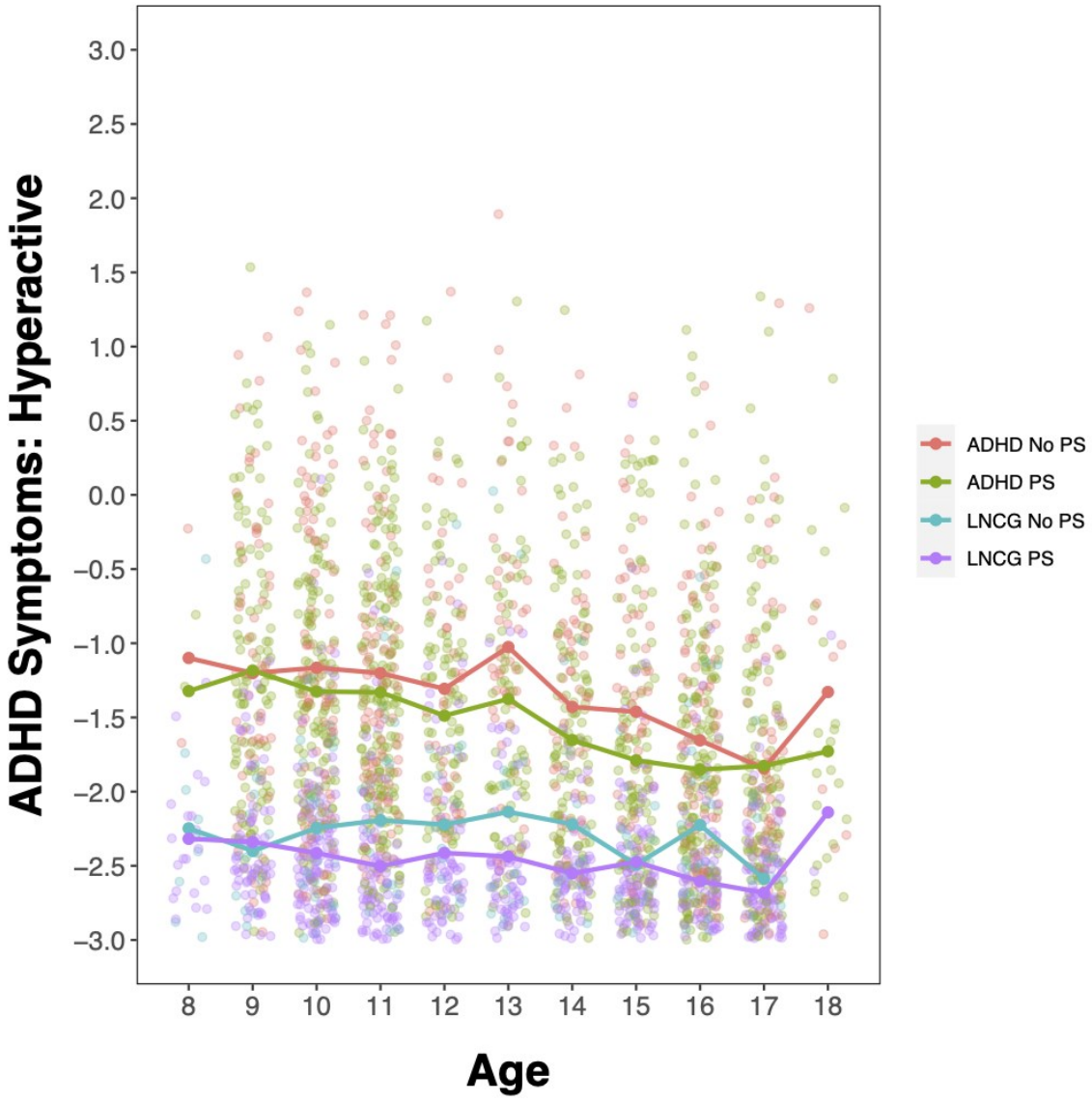


Table 4.4

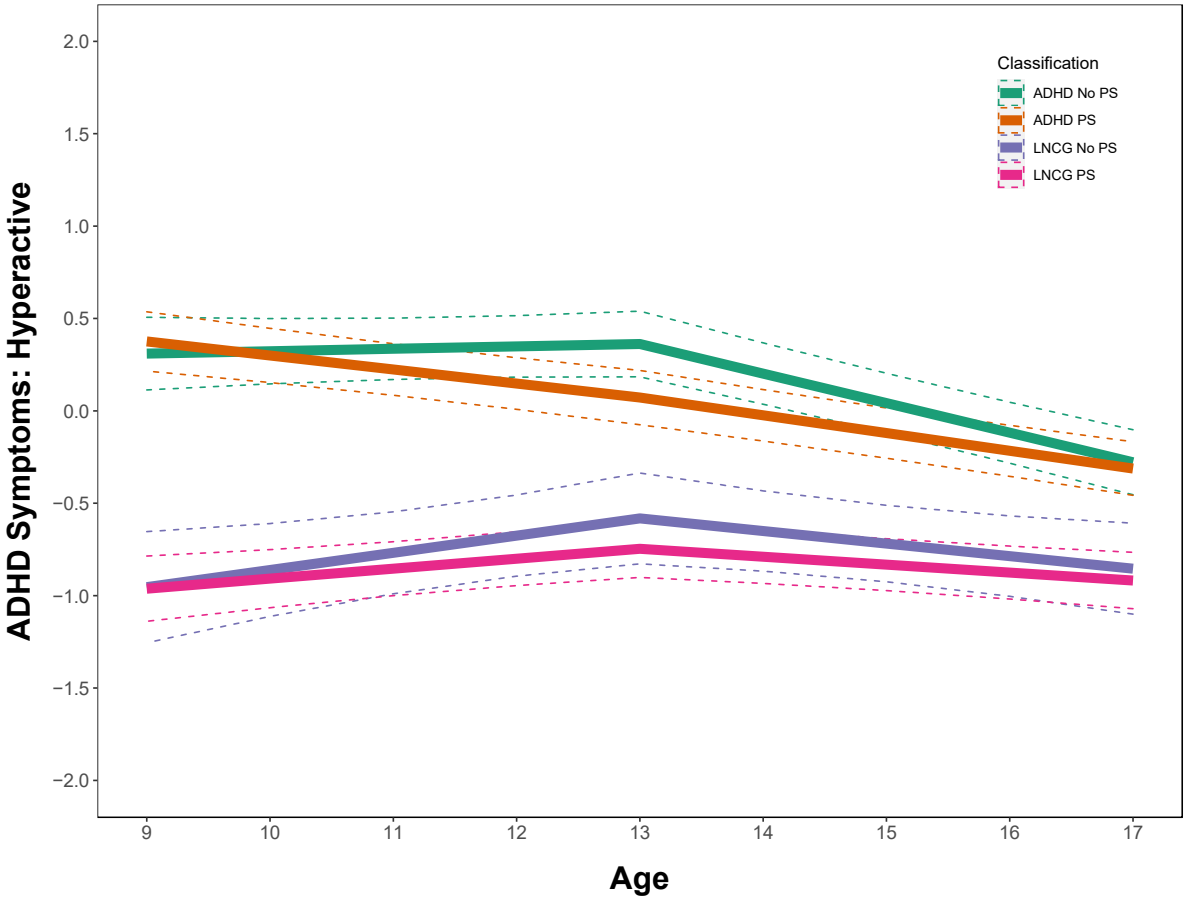
Hyperactive Symptoms Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	-0.582*	0.150	-0.693*	0.178
ADHD	0.944*	0.146	0.532*	0.081
Post-Secondary	-0.164	0.143	-0.089	0.078
ADHD*Post-Secondary	-0.126	0.165	-0.075	0.097
Rate of Change (Slope Age 9-13)	0.093	0.049	0.461	0.245
ADHD	-0.080	0.056	-0.189	0.132
Post-Secondary	-0.039	0.055	-0.087	0.125
ADHD*Post-Secondary	-0.050	0.064	-0.123	0.157
Rate of Change (Slope Age 13-17)	-0.068	0.041	-0.447	0.272
ADHD	-0.092*	0.046	-0.285*	0.146
Post-Secondary	0.025	0.045	0.074	0.134
ADHD*Post-Secondary	0.039	0.052	0.127	0.170
Covariates				
Sex (Male)	0.092	0.058	0.044	0.028
Treatment Site 2	0.004	0.041	0.003	0.036
Treatment Site 3	0.062*	0.031	0.081*	0.040
Treatment Site 4	0.030	0.020	0.055	0.037
Treatment Site 5	0.022	0.016	0.050	0.036
Treatment Site 6	-0.005	0.013	-0.012	0.036
Ethnicity: Black	0.151*	0.073	0.066*	0.032
Ethnicity: Hispanic	-0.002	0.094	-0.001	0.033
Ethnicity: Other	0.042	0.080	0.015	0.029
Advantaged	0.018	0.052	0.010	0.030
Low-Income Status	-0.012	0.105	-0.004	0.032
Externalizing Disorder	0.344*	0.055	0.178*	0.029
Age of Mom at Birth	0.001	0.004	0.004	0.030
Social Assistance Income	0.165*	0.075	0.071*	0.033
Medication Management	-0.082	0.058	-0.040	0.028
Multimodal Superiority	0.014	0.040	0.009	0.027
Behavioural Substitution	0.007	0.040	0.004	0.027

*$p < .05$

Figure 4.6

Implied Trajectories for Hyperactive Symptoms by Age and Group with 90% Confidence Bands



Overall, ADHD histories were associated with hyperactive symptoms at age 13; post-secondary enrolment was not. At age 13, adolescents with ADHD histories had higher levels of hyperactive symptoms than the LNCG. Among those with ADHD histories, hyperactive symptoms were slightly higher at age 13 for those who did not eventually enrol in post-secondary studies. However, the confidence bands overlap so the difference between those who did and did not eventually enrol in post-secondary studies is not significant. Similarly, within the LNCG, hyperactive symptoms were slightly higher at age 13 among those who did not eventually enrol in post-secondary studies, but the differences are not significant. From ages 9-13, neither ADHD symptoms nor post-secondary enrolment were associated with the rate of change in hyperactive symptoms. From ages 13-17, the ADHD groups experienced a decline in hyperactive symptoms. Overall, there were mean-level group differences in hyperactive symptoms at age 13 and the rate of change differed from ages 13-17 for those with versus without ADHD histories.

The pattern in Figure 4.6 shows that, from ages 9-17, adolescents with ADHD histories had higher levels of hyperactive symptoms than the LNCG. From ages 9-13, the trajectories for all four groups were relatively flat. This suggests that in the early years, hyperactive symptoms remain relatively stable. From ages 13-17, the trajectories were approximately flat for the LNCG whereas they declined for the ADHD histories groups. Overall, ADHD histories were associated with hyperactive symptoms at age 13 and the rate of change from ages 13-17. Post-secondary enrolment was not significantly associated with hyperactive symptoms at age 13 nor the rates of change from ages 9-17.

Discussion: ADHD Symptoms

I examined the developmental trajectories of inattentive and hyperactive ADHD symptoms from ages 9 through 17, considering the effects of ADHD histories and post-secondary enrolment. Consistent with the existing literature, inattentive symptoms persisted whereas hyperactive symptoms were minimal by adolescence (Wasserstein, 2005). In an MTA study examining inattentive and hyperactive symptoms from baseline to Year 8, there was a steep decline in symptom severity during the treatment phase, especially within the first three months of treatment (Howard et al., 2015). After treatment, hyperactive symptoms continued to slowly decline whereas inattentive symptoms remained steady. Similar to the present research, inattentive symptom levels were higher after treatment than hyperactive symptom levels and remained relatively stable over time whereas hyperactive symptoms declined in adolescence.

Furthermore, as predicted, adolescents with ADHD histories reported higher levels of ADHD symptoms, both hyperactive and inattentive, at all ages. Thus, even after treatment, adolescents with ADHD histories continued to experience more severe ADHD symptoms. In the adolescent years the difference in reported symptom levels for those with and without ADHD histories narrowed, but there was still a significant difference between the two groups. This finding is consistent with a study investigating parent-rated impairment factors among adolescents with ADHD histories and the LNCG (Howard et al., 2016). Howard et al. found that although adolescents with ADHD histories experienced greater impairment in comparison to the LNCG, those with ADHD who eventually attended college did not have higher levels of impairment than those who did not eventually attend. In summary, although adolescents with ADHD histories continued

to experience more severe symptomology than the LNCG, the trajectories of ADHD symptoms did not significantly differ among adolescents with ADHD histories who did and did not attend post-secondary education.

Interestingly, in a previous study using MTA data, Hechtman et al. (2016) found that when adults with ADHD histories were divided into symptom-persistent (i.e., the presence of fewer than five symptoms of ADHD) and symptom-desistent (i.e., the presence of five or more symptoms of ADHD) groups, the symptom-persistent group was less likely to obtain a degree than the symptom-desistent group. Both groups were less likely to obtain a degree than the LNCG. In Hechtman et al.'s study, symptoms of ADHD were measured in adulthood, and they did not consider the severity of the symptoms, but rather just the presence of symptoms. In the present study, parents and teachers reported on the severity of symptoms. When measured this way, there was no significant difference in reported symptoms for adolescents with ADHD histories who did and did not eventually enrol in post-secondary studies. As discussed in the previous section, all four treatment groups had a significant reduction in ADHD symptoms during the study (MTA Cooperative Group, 1999a). Thus, the similar symptom levels across the groups, especially in adolescence, are likely a reflection of the effective ADHD treatment.

In summary, adolescents with ADHD histories had more severe ADHD symptoms, both inattentive and hyperactive, than those with no history of ADHD. Among those with ADHD histories, neither mean levels or rates of change in inattentive nor hyperactive symptoms significantly differed for those who did versus did not eventually enrol in post-secondary studies. However, although not significant, in examining the patterns of the graphs it appears that the ADHD No-Post Secondary group,

on average, reported experiencing more severe inattentive symptoms than the ADHD Post-Secondary group and that the symptoms increased from ages 9-13. Thus, higher, more consistent levels of inattentive symptoms may be present in adolescents with ADHD histories who do not attend post-secondary studies.

CHAPTER 5: DEVELOPMENTAL TRAJECTORIES OF ACADEMIC OUTCOMES

In this chapter the results of the latent curve modelling analyses for academic outcomes (i.e., academic achievement and school performance) are presented. The goal was to address the following question: Do the trajectories of academic outcomes differ for the four groups of adolescents, that is, those with or without ADHD histories who did or did not attend post-secondary education?

Academic Achievement

Mathematics Academic Achievement

Table 5.1 shows the number of participants and the means and standard deviations for WIAT math scores from ages 8-18. Figure 5.1 shows box plots of WIAT math scores at each age. Figure 5.2 shows both the individual and average WIAT math scores for each age, separated by group. Based on Figures 5.1 and 5.2, the slopes appeared to be relatively stable from ages 8- 18 with no obvious peaks. Thus, linear latent curve modelling was used to model trajectories with the intercept placed at age 13. The final model, which included the covariates, had good fit, $\chi^2(197) = 318.97$, $p < .001$, SRMR = .060, CFI = .958, RMSEA = .029 [.023, .035]. See Table 5.2 for a summary of the unstandardized and standardized model results. See Figure 5.3 for the implied trajectories for the four groups.

Table 5.1

Means and Standard Deviations for WIAT Math at Each Age, Separated by Group

	Age (in Years)										
	8	9	10	11	12	13	14	15	16	17	18
ADHD Post-Secondary											
N	3	119	169	183	98	89	109	127	165	126	144
Mean	107	104	104	104	104	101	100	99	99	96	91
SD	34	15	14	16	18	15	15	17	16	17	14
ADHD No Post-Secondary											
N	3	61	97	100	55	48	54	58	85	65	49
Mean	88	97	97	92	91	93	90	88	87	86	77
SD	2	13	13	13	12	14	15	15	15	15	15
LNCG Post-Secondary											
N	21	69	118	104	76	64	72	90	84	96	82
Mean	110	110	113	114	114	111	108	112	108	107	102
SD	16	16	15	17	15	14	16	15	16	14	15
LNCG No Post-Secondary											
N	10	15	27	21	17	17	17	18	21	17	13
Mean	106	98	100	94	100	95	92	95	94	93	81
SD	12	12	13	11	13	11	14	14	17	15	12

Figure 5.1

Box Plots and Scatterplots Showing WIAT Math Scores by Age

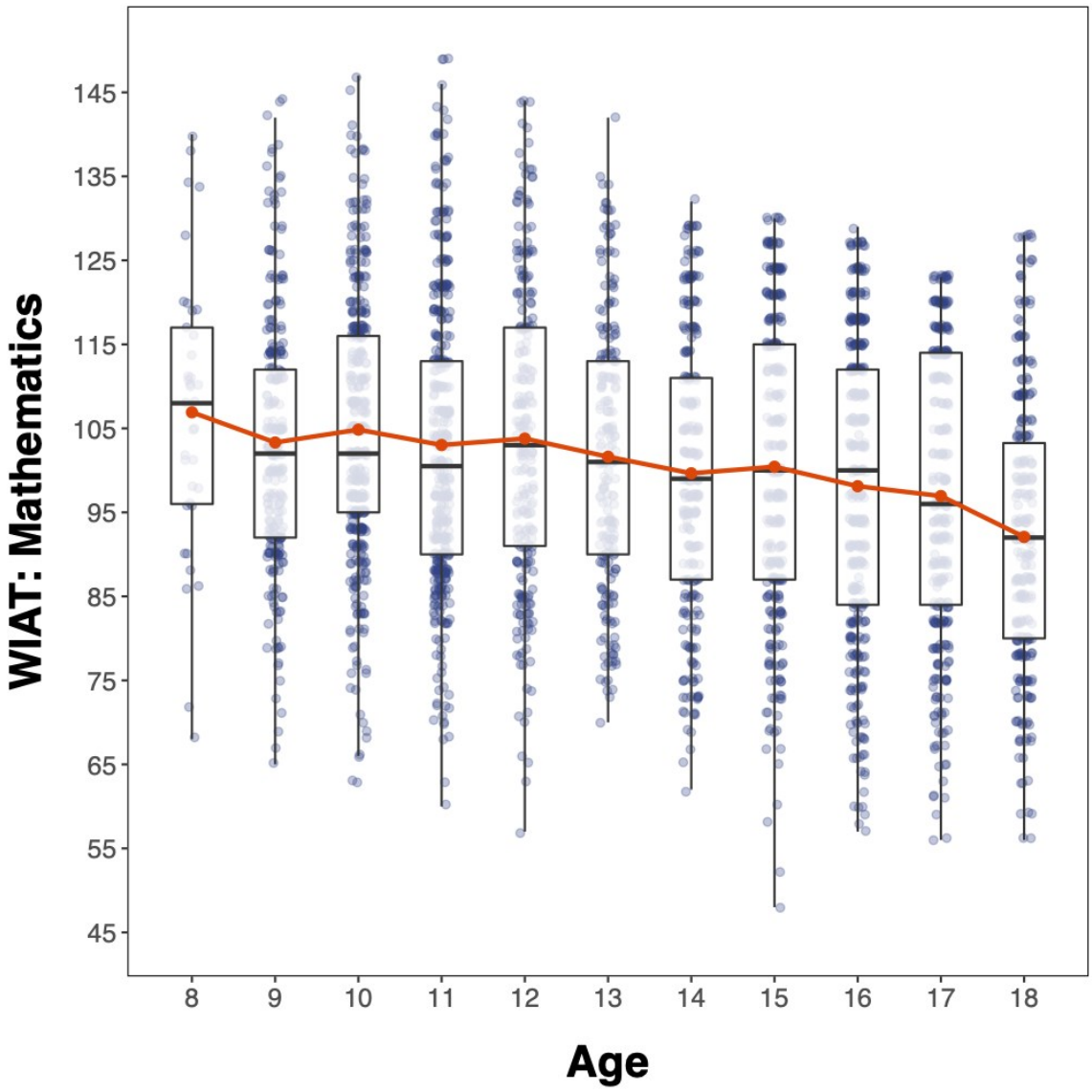


Figure 5.2

Individual and Mean Scores for WIAT Math Scores by Age and Group

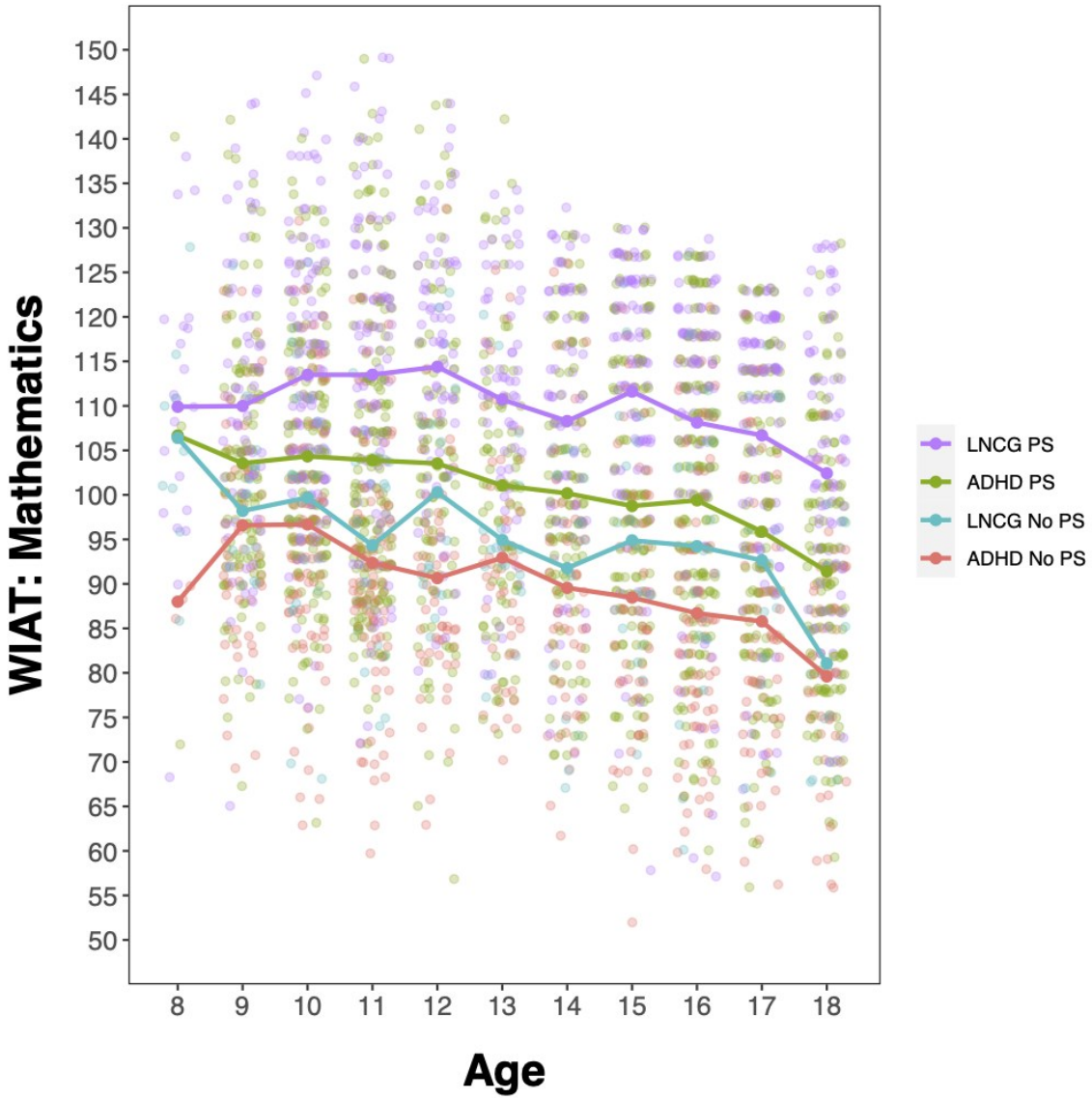


Table 5.2

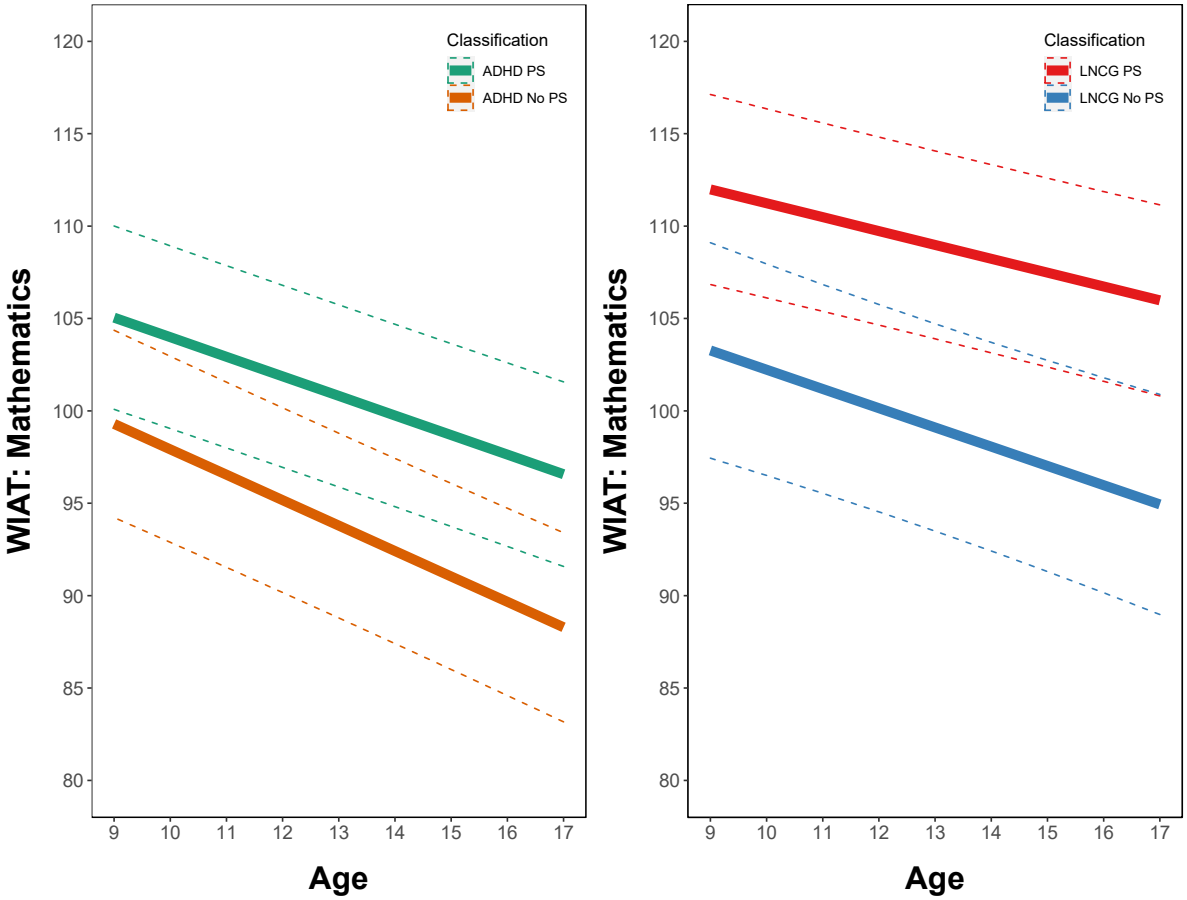
WIAT Math Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	99.104*	3.420	6.564*	0.295
ADHD	-5.312*	2.095	-0.166*	0.066
Post-Secondary	9.879*	2.086	0.298*	0.063
ADHD*Post-Secondary	-2.861	2.357	-0.094	0.077
Rate of Change (Slope Age 9-17)	-1.042*	0.276	-0.823*	0.222
ADHD	-0.334	0.312	-0.125	0.116
Post-Secondary	0.292	0.305	0.105	0.110
ADHD*Post-Secondary	0.025	0.353	0.010	0.138
Covariates				
Sex (Male)	2.508*	1.142	0.067*	0.030
Treatment Site 2	-0.638	0.833	-0.031	0.040
Treatment Site 3	0.529	0.618	0.038	0.045
Treatment Site 4	-0.759	0.402	-0.078	0.041
Treatment Site 5	0.603	0.318	0.076	0.040
Treatment Site 6	-0.363	0.276	-0.054	0.041
Ethnicity: Black	-9.911*	1.463	-0.244*	0.036
Ethnicity: Hispanic	-6.700*	1.898	-0.132*	0.037
Ethnicity: Other	-4.370*	1.600	-0.087*	0.032
Advantaged	-7.240*	1.030	-0.236*	0.033
Low-Income Status	-1.630	2.107	-0.028	0.036
Externalizing Disorder	-0.406	1.116	-0.012	0.032
Age of Mom at Birth	0.201*	0.084	0.080*	0.034
Social Assistance Income	0.678	1.511	0.016	0.036
Medication Management	-0.177	1.127	-0.005	0.030
Multimodal Superiority	0.906	0.791	0.035	0.030
Behavioural Substitution	1.050	0.802	0.040	0.030

*$p < .05$

Figure 5.3

Implied Trajectories for WIAT Math by Age and Group with 90% Confidence Bands



Overall, both ADHD histories and eventual post-secondary enrolment were associated with WIAT math scores at age 13. At age 13, adolescents with ADHD histories had lower math achievement scores than the LNCG. Similarly, at age 13, adolescents who did not eventually attend post-secondary studies had lower math achievement scores than those who did. Within the ADHD histories groups, Figure 5.3 shows that that the ADHD Post-Secondary group continuously had higher math achievement scores than the ADHD No Post-Secondary group. However, there is some overlap in confidence bands, so this difference is not significant. Similarly, within the LNCG, adolescents who attended post-secondary education had higher math achievement scores than those who did not. Again, however, the confidence bands overlap. Neither ADHD symptoms nor post-secondary enrolment were associated with the rate of change in WIAT math scores, although in general there was a slight decline in math achievement scores over time. In summary, there were mean-level group differences in math achievement for those with versus without ADHD histories and those who did versus those who did not eventually enrol in post-secondary studies, but the groups did not change differently over time.

Reading Academic Achievement

Table 5.3 shows the number of participants and the means and standard deviations for WIAT reading scores from ages 8-18. Figure 5.4 shows box plots of WIAT reading scores at each age. Figure 5.5 shows both the individual and average WIAT reading scores for each age, separated by group. Based on Figures 5.4 and 5.5, the slopes appeared to be relatively stable from ages 8-18 with no obvious peaks. Thus, linear latent curve modelling was used to model trajectories with the intercept placed at age 13. The final model, which included the covariates, had good fit, $\chi^2(197) = 278.99$, $p < .001$, SRMR = .047, CFI = .973, RMSEA = .024 [.017, .030]. See Table 5.4 for a summary of the unstandardized and standardized model results. See Figure 5.6 for the implied trajectories for the four groups.

Table 5.3

Means and Standard Deviations for WIAT Reading at Each Age, Separated by Group

	Age (in Years)										
	8	9	10	11	12	13	14	15	16	17	18
ADHD Post-Secondary											
N	3	119	169	183	98	89	109	127	165	126	144
Mean	91	99	102	101	98	100	98	99	98	98	101
SD	11	14	13	13	14	11	12	12	12	12	12
ADHD No Post-Secondary											
N	3	61	97	100	55	48	54	58	85	65	49
Mean	85	997	94	92	94	93	90	90	87	89	92
SD	10	13	14	14	13	14	15	15	15	12	18
LNCG Post-Secondary											
N	21	69	118	104	76	64	72	90	84	96	82
Mean	110	107	108	107	107	104	104	105	103	101	107
SD	17	14	13	11	10	11	12	12	11	10	10
LNCG No Post-Secondary											
N	10	15	27	21	17	17	17	18	21	17	13
Mean	106	98	100	99	99	95	95	96	94	94	97
SD	11	12	15	16	12	14	15	12	12	9	14

Figure 5.4

Box Plots and Scatterplots Showing WIAT Reading Scores by Age

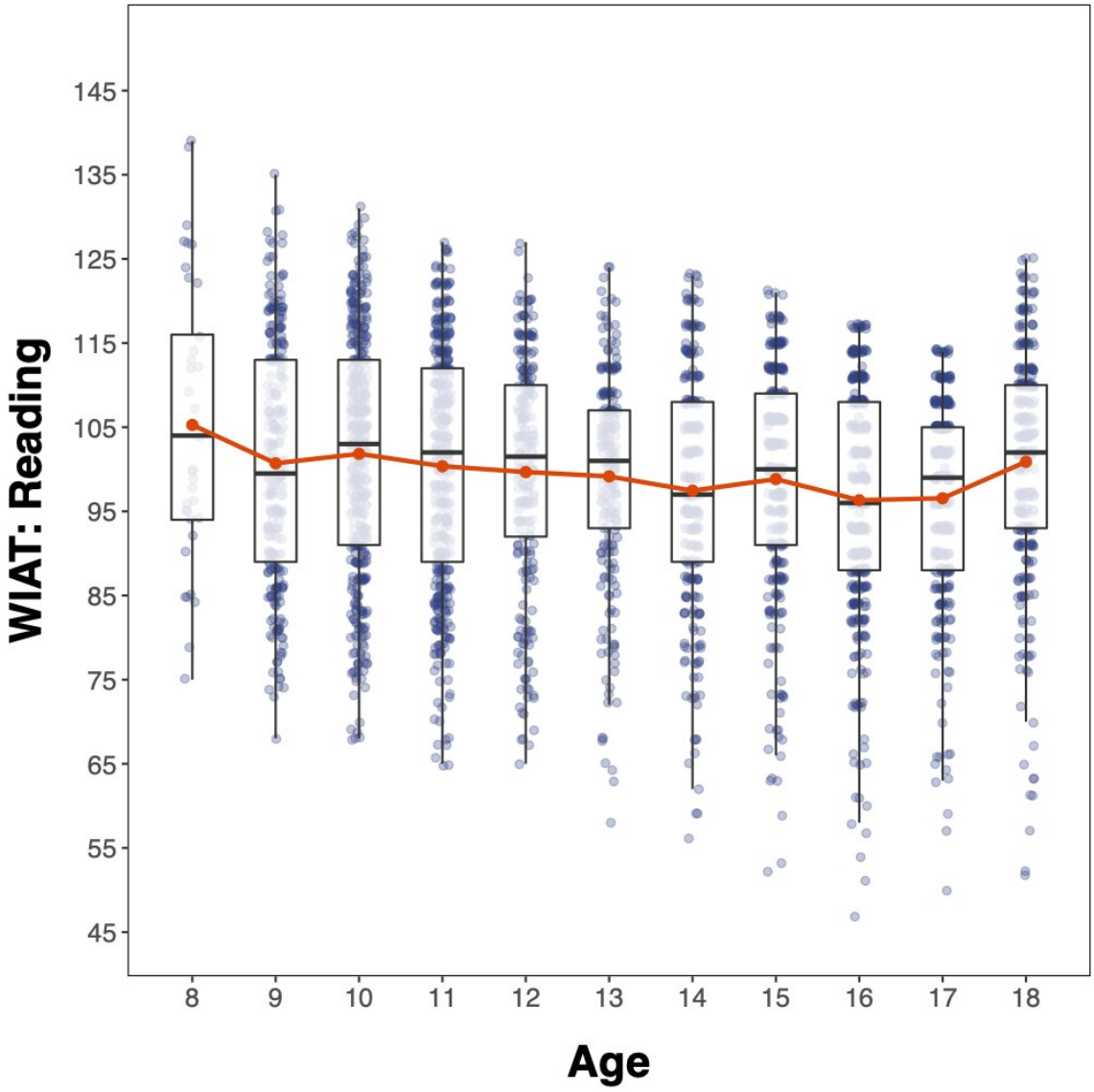


Figure 5.5

Individual and Mean Scores for WIAT Reading Scores by Age and Group

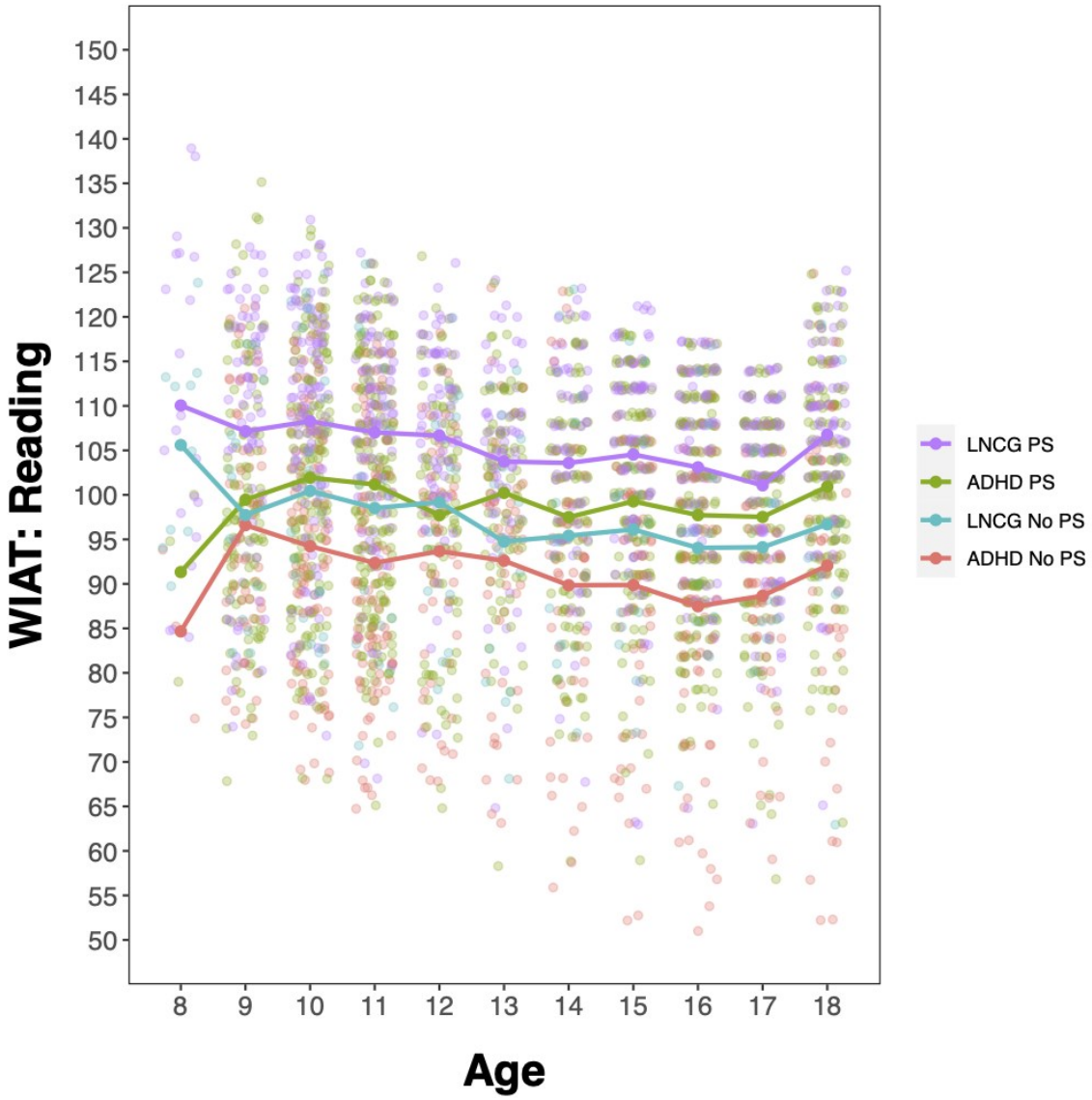


Table 5.4

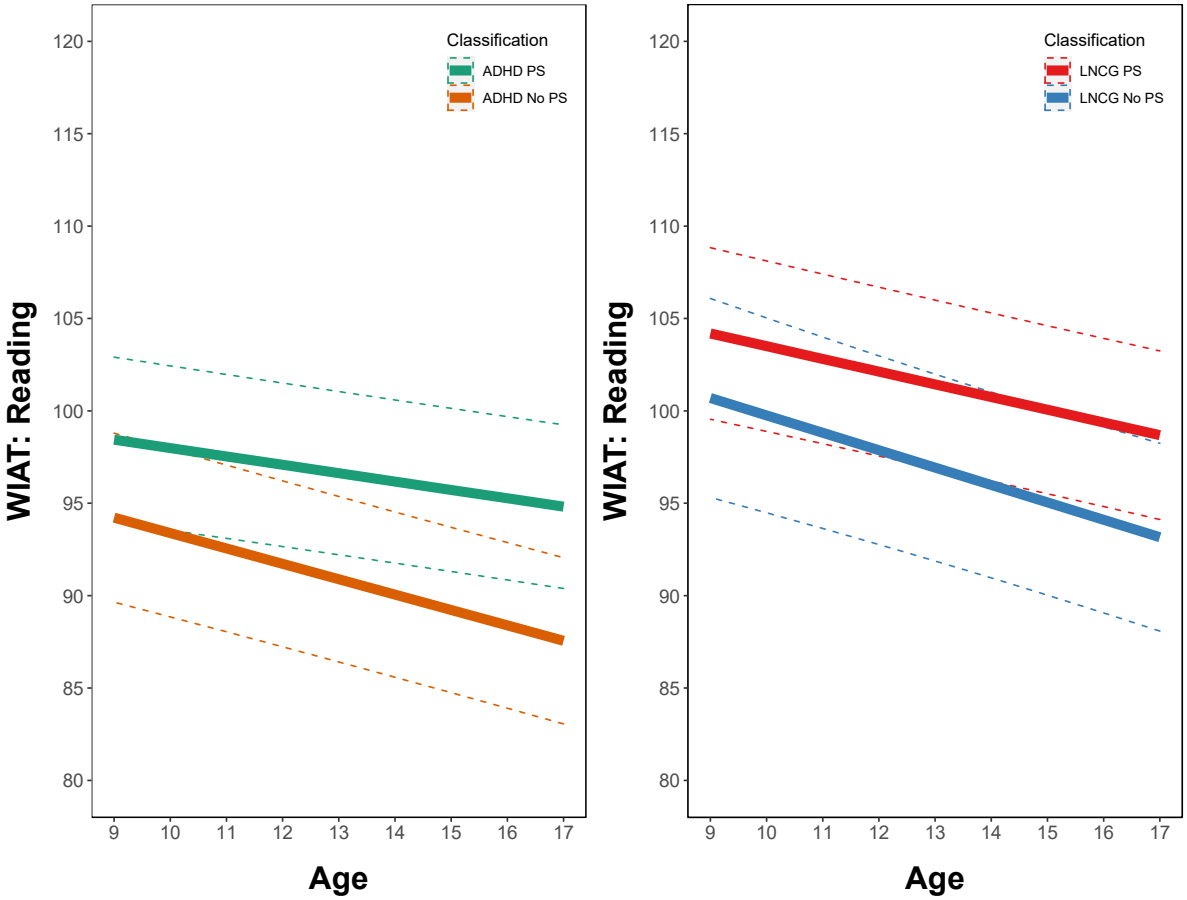
WIAT Reading Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	96.932*	3.082	7.677*	0.326
ADHD	-6.042*	1.913	-0.226*	0.071
Post-Secondary	4.505*	1.904	0.163*	0.069
ADHD*Post-Secondary	1.234	2.152	0.048	0.084
Rate of Change (Slope Age 9-17)	-0.942*	0.208	-0.992*	0.223
ADHD	0.109	0.235	0.054	0.117
Post-Secondary	0.254	0.230	0.122	0.110
ADHD*Post-Secondary	0.126	0.266	0.066	0.139
Covariates				
Sex (Male)	1.813	1.020	0.058	0.032
Treatment Site 2	1.486*	0.74	0.085*	0.042
Treatment Site 3	0.376	0.552	0.033	0.048
Treatment Site 4	-0.245	0.356	-0.030	0.044
Treatment Site 5	0.106	0.284	0.016	0.043
Treatment Site 6	0.226	0.240	0.040	0.043
Ethnicity: Black	-6.936*	1.309	-0.204*	0.038
Ethnicity: Hispanic	-2.753	1.687	-0.065	0.040
Ethnicity: Other	-1.969	1.430	-0.047	0.034
Advantaged	-4.579*	0.921	-0.179*	0.036
Low-Income Status	-1.972	1.885	-0.040	0.038
Externalizing Disorder	0.092	0.997	0.003	0.034
Age of Mom at Birth	0.158*	0.076	0.075*	0.036
Social Assistance Income	0.808	1.350	0.023	0.039
Medication Management	0.083	1.010	0.003	0.033
Multimodal Superiority	0.269	0.709	0.012	0.033
Behavioural Substitution	0.919	0.717	0.042	0.032

*$p < .05$

Figure 5.6

Implied Trajectories for WIAT Reading by Age and Group with 90% Confidence Bands



Similar to mathematics, both ADHD histories and eventual post-secondary enrolment were associated with WIAT reading scores at age 13. At age 13, adolescents with ADHD histories had lower reading achievement scores than the LNCG. Similarly, at age 13, adolescents who did not eventually attend post-secondary studies had lower reading achievement scores than those who did. Within the ADHD histories groups, Figure 5.6 shows that the ADHD Post-Secondary group had higher reading achievement scores than the ADHD No Post-Secondary group. The LNCG Post-Secondary had higher reading achievement than the LNCG No Post-Secondary. However, for both the ADHD histories groups and the LNCG, the confidence bands overlap so the differences were not significant. Neither ADHD symptoms nor post-secondary enrolment were associated with the rate of change in WIAT reading scores. In summary, there were mean-level group differences in reading achievement for those with versus without ADHD histories and those who did versus those who did not eventually enrol in post-secondary studies, but the groups did not change differently over time; reading achievement appears to be stable from ages 9-17.

Spelling Academic Achievement

Table 5.5 shows the number of participants and the means and standard deviations for WIAT spelling scores from ages 8-18. Figure 5.7 shows box plots of WIAT spelling scores at each age. Figure 5.8 shows both the individual and average WIAT spelling scores for each age, separated by group. Based on Figures 5.7 and 5.8, the slopes appeared to be relatively stable from ages 8-18 with no obvious peaks. Thus, linear latent curve modelling was used to model trajectories with the intercept placed at age 13. The final model, which included the covariates, had good fit, $\chi^2(197) = 324.59$, $p < .001$, SRMR = .038, CFI = .961, RMSEA = .030 [.024, .036]. See Table 5.6 for a summary of the unstandardized and standardized model results. See Figure 5.9 for the implied trajectories for the four groups.

Table 5.5

Means and Standard Deviations for WIAT Spelling at Each Age, Separated by Group

	Age (in Years)										
	8	9	10	11	12	13	14	15	16	17	18
ADHD Post-Secondary											
N	3	119	169	183	98	89	109	127	165	126	144
Mean	93	97	99	97	93	95	95	96	95	96	98
SD	20	14	14	14	15	14	15	15	15	15	14
ADHD No Post-Secondary											
N	3	61	97	100	55	48	54	58	85	65	49
Mean	94	94	91	88	88	89	85	83	83	83	85
SD	19	12	12	14	13	15	14	15	16	15	19
LNCG Post-Secondary											
N	21	69	118	104	76	64	72	90	84	96	82
Mean	110	105	106	105	104	102	104	104	102	103	105
SD	17	14	13	12	13	15	14	14	15	13	11
LNCG No Post-Secondary											
N	10	15	27	21	17	17	17	18	21	17	13
Mean	106	94	99	94	99	92	97	99	93	96	95
SD	9	13	11	13	11	13	15	13	13	11	12

Figure 5.7

Box Plots and Scatterplots Showing WIAT Spelling Scores by Age

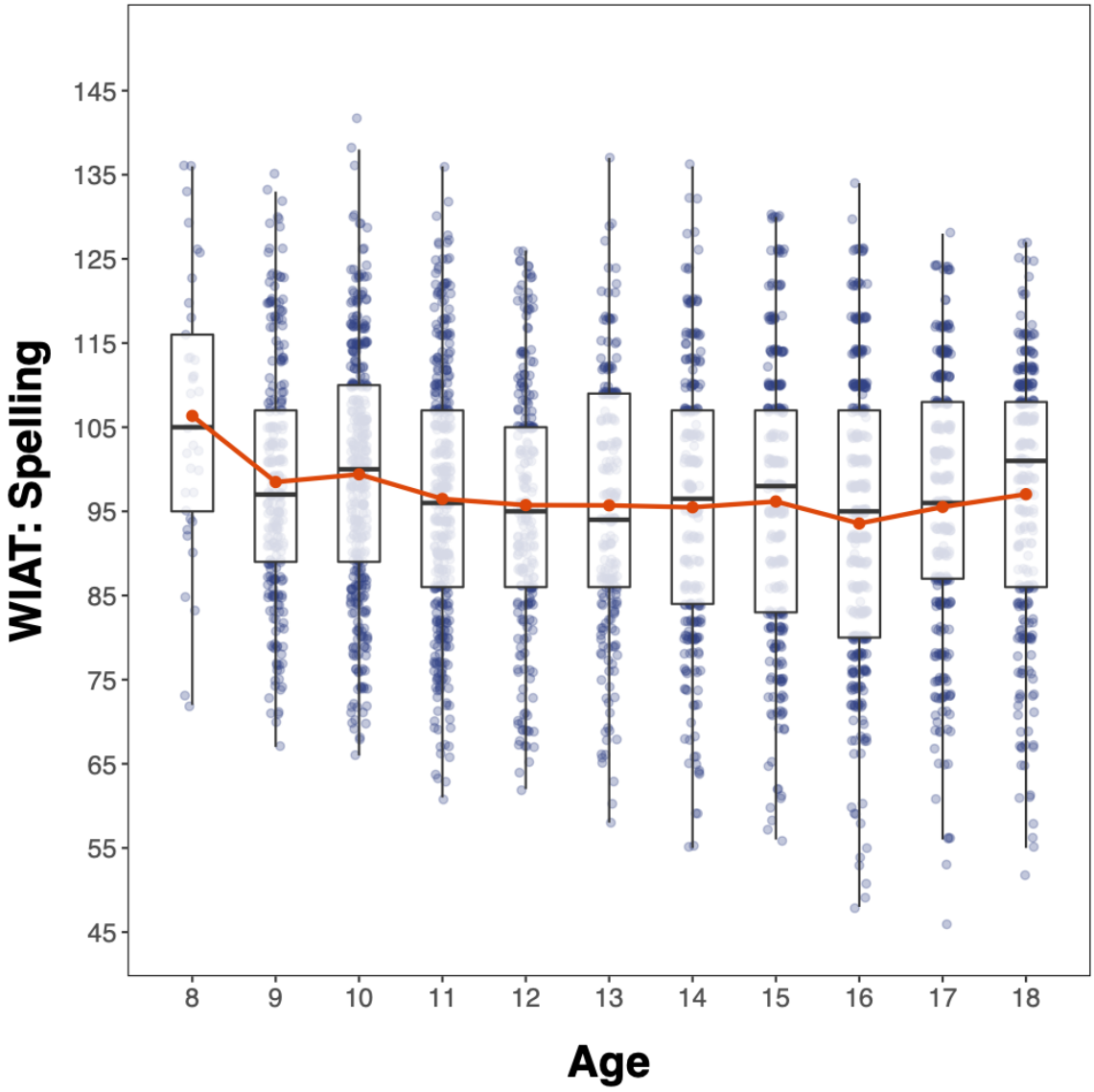


Figure 5.8

Individual and Mean Scores for WIAT Spelling Scores by Age and Group

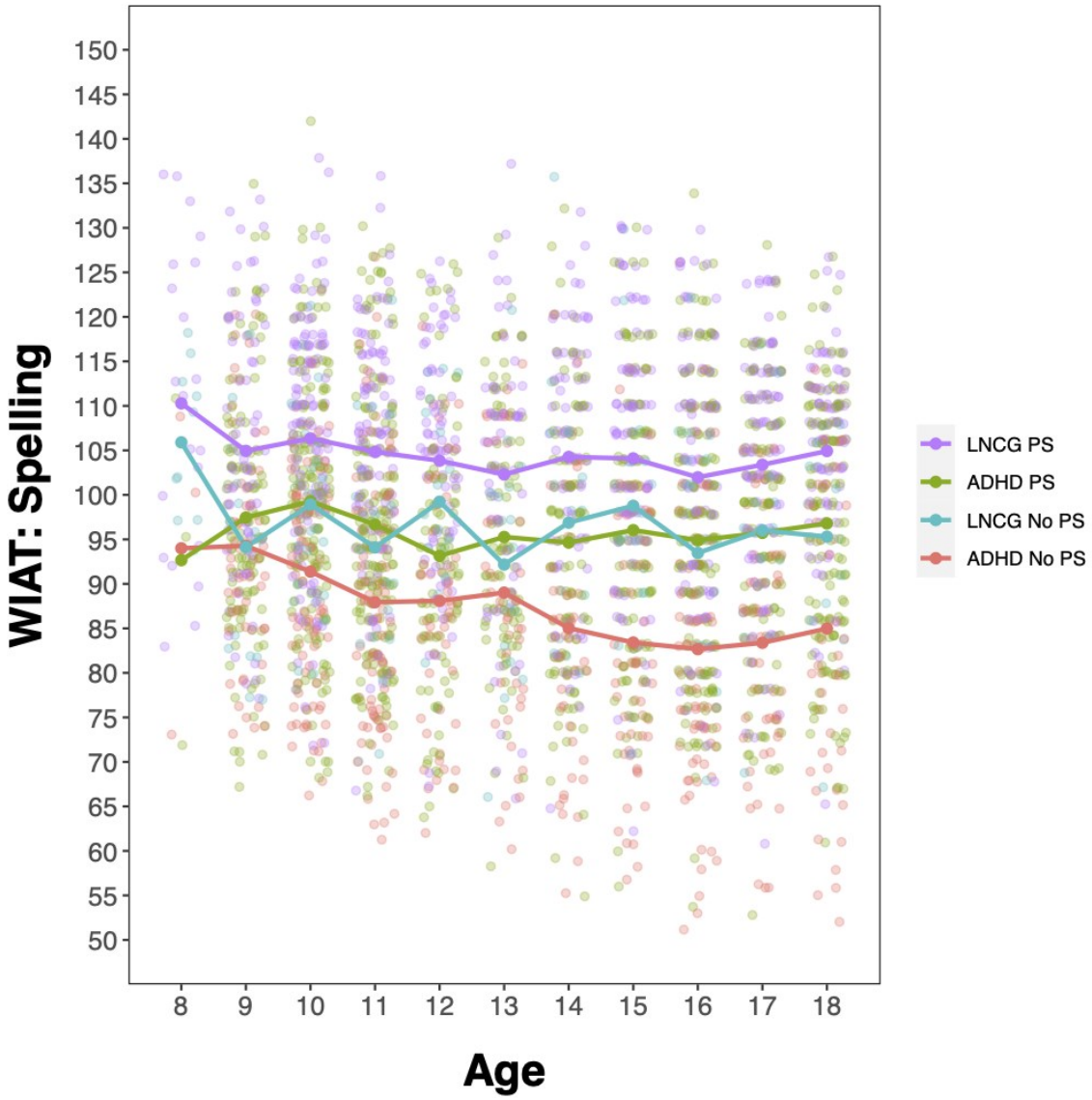


Table 5.6

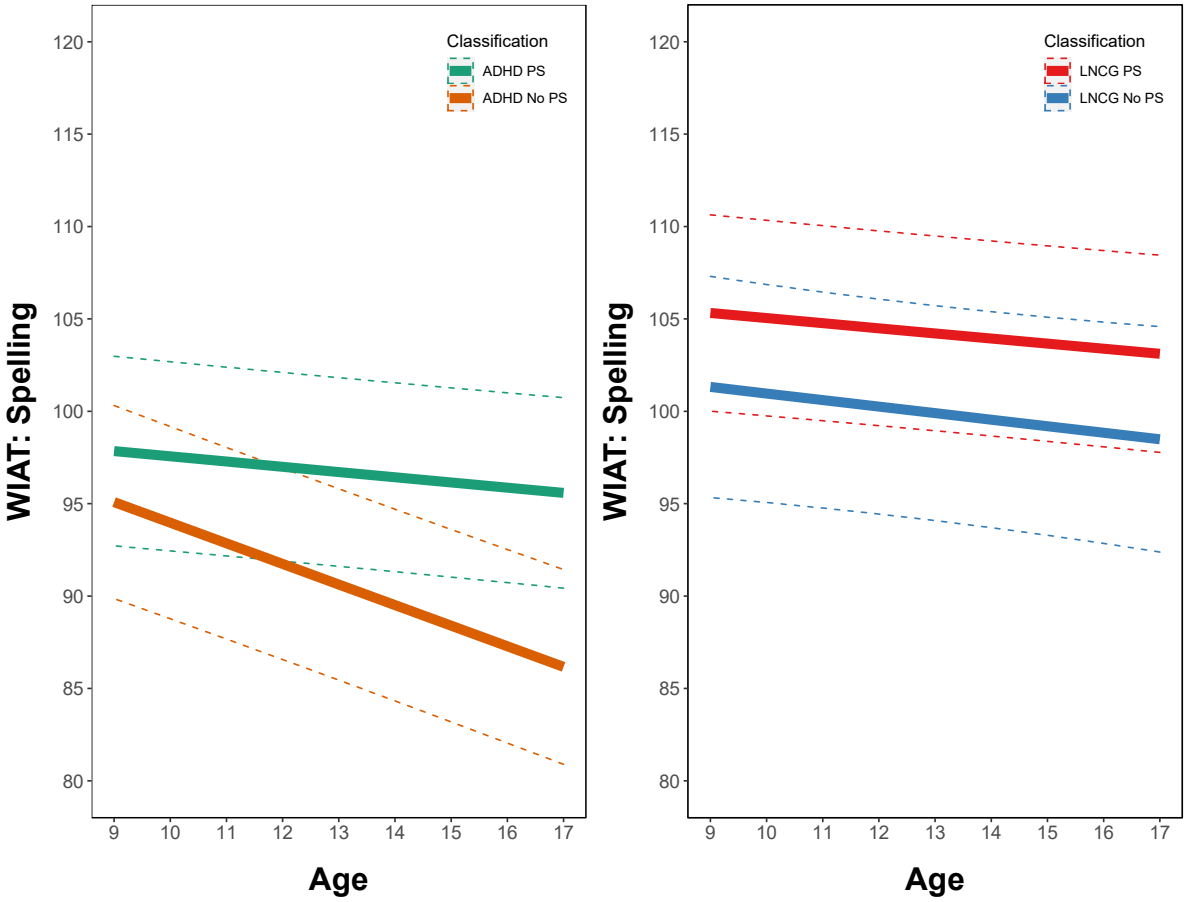
WIAT Spelling Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	99.901*	3.546	6.980*	0.306
ADHD	-9.272*	2.173	-0.307*	0.071
Post-Secondary	4.316*	2.165	0.137*	0.069
ADHD*Post-Secondary	1.770	2.443	0.061	0.084
Rate of Change (Slope Age 9-17)	-0.354	0.250	-0.269	0.190
ADHD	-0.761*	0.282	-0.274*	0.101
Post-Secondary	0.078	0.275	0.027	0.096
ADHD*Post-Secondary	0.754*	0.319	0.284*	0.120
Covariates				
Sex (Male)	-0.218	1.184	-0.006	0.033
Treatment Site 2	0.402	0.857	0.020	0.043
Treatment Site 3	0.082	0.640	0.006	0.049
Treatment Site 4	-0.928*	0.416	-0.101*	0.045
Treatment Site 5	0.145	0.330	0.019	0.044
Treatment Site 6	-0.377	0.281	-0.059	0.044
Ethnicity: Black	-3.801*	1.508	-0.099*	0.039
Ethnicity: Hispanic	-1.440	1.952	-0.030	0.040
Ethnicity: Other	-1.142	1.652	-0.024	0.035
Advantaged	-6.168	1.067	-0.212	0.036
Low-Income Status	-2.420	2.174	-0.043	0.039
Externalizing Disorder	-0.327	1.157	-0.010	0.035
Age of Mom at Birth	0.146	0.087	0.061	0.037
Social Assistance Income	1.768	1.564	0.045	0.039
Medication Management	1.189	1.165	0.034	0.033
Multimodal Superiority	-0.104	0.819	-0.004	0.033
Behavioural Substitution	0.547	0.830	0.022	0.033

*$p < .05$

Figure 5.9

Implied Trajectories for WIAT Spelling by Age and Group with 90% Confidence Bands



Overall, both ADHD histories and eventual post-secondary enrolment were associated with WIAT spelling scores at age 13. At age 13, adolescents with ADHD histories had lower spelling achievement scores than the LNCG. Similarly, at age 13, adolescents who did not eventually attend post-secondary studies had lower spelling achievement scores than those who did. Within the ADHD histories group, Figure 5.9 shows that, at age 13, the ADHD Post-Secondary group had higher spelling achievement scores than the ADHD No Post-Secondary group, but the confidence bands overlap so this difference was not significant. Similarly, at age 13, the LNCG Post-Secondary had higher spelling achievement scores than the LNCG No Post-Secondary. Again, however, the confidence bands overlap.

ADHD histories were associated with the rate of change in WIAT spelling scores. Furthermore, the ADHD by post-secondary interaction was associated with the rate of change in WIAT spelling scores. Thus, the rate of change in spelling achievement was different for those with ADHD histories who eventually enrolled in post-secondary studies compared to those who did not eventually enrol. For the LNCG, rates of change were similar for those who did versus those who did not eventually enrol in post-secondary studies.

Discussion: Academic Achievement

Three developmental trajectories of academic achievement were considered in the present research: mathematics, reading, and spelling. ADHD is associated with learning difficulties that negatively affect several academic areas, including reading, writing, and mathematics (Dupaul et al., 2013; Frazier et al., 2007). Consistent with these findings, as predicted, compared to the LNCG, the ADHD histories group had lower academic

achievement in mathematics, reading, and spelling. The literature suggests that people with ADHD score, on average, 11 points lower than their typically developing peers on measures of achievement (i.e., 89 points vs. 100 points; Frazier et al., 2007). This deficit was observed in the present study. However, when considering the four groups, different patterns emerged. The ADHD Post-Secondary group had similar mean achievement scores to the LNCG No Post-Secondary across all grades. The ADHD No Post-Secondary group had the lowest achievement scores, and at several ages had mean scores that were below 89. In contrast, the LNCG Post-Secondary often had mean scores above 100. Thus, while on average students with ADHD are more likely to have lower academic achievement than their typically developing peers, the developmental trajectories highlight the different patterns for those who did versus did not eventually enrol in post-secondary education.

In examining the trajectories, in general, adolescents with ADHD histories had lower academic achievement in mathematics, readings, and spelling at age 13 than those without ADHD histories. Similarly, adolescents who did not eventually enrol in post-secondary studies had lower academic achievement in mathematics, reading, and spelling at age 13 than those who did eventually enrol. Although there was not a significant interaction between ADHD histories and post-secondary enrolment, based on the graphed trajectories it is evident that the ADHD Post-Secondary group have academic achievement trajectories that are more similar to the LNCG No Post-Secondary than the ADHD No Post-Secondary group. Based on these trajectories, by adolescence some people with ADHD histories caught up to their typically developing peers (Loe &

Feldman, 2007), but overall the academic achievement of the ADHD Post-Secondary group was lower than the LNCG Post-Secondary.

With respect to changes in academic achievement over time, I hypothesized relatively flat slopes for each of the four groups for mathematics, reading, and spelling achievement because academic achievement is a stable construct (Chen et al., 2014; Kowaleski-Jones & Duncan, 1999; Wright, 2010). In general, this hypothesis was supported: Academic achievement was relatively stable, with all four groups experiencing a slight decline as they got older. With the exception of spelling, the rate of change in academic achievement did not differ across the four groups.

Only the slope of spelling achievement significantly differentiated the ADHD Post-Secondary and ADHD No Post-Secondary groups. However, in examining the three academic achievement slopes, adolescents in the ADHD No Post-Secondary group are not experiencing a greater decline in spelling achievement over time in comparison to mathematics and reading achievement. In general, there was a decrease of between 5-10 points for all three academic achievement measures from ages 9-17. Thus, the slope does not reflect a difference in spelling abilities compared to mathematics and reading abilities among the ADHD No Post-Secondary group. Instead, the trajectories show that for the other three groups spelling trajectories were quite stable, almost flat, from ages 9-17, whereas mathematics and reading trajectories slightly declined. Thus, the ADHD No Post-Secondary group did not have worse spelling achievement compared to their mathematics and reading achievement, but rather their spelling achievement declined whereas the other three groups remained stable.

As discussed previously, persons with ADHD struggle in many areas of study (Dupaul et al., 2013; Frazier et al., 2007). Why then was there a difference in spelling achievement for the ADHD No Post-Secondary group? Although there is limited research available on ADHD and written expression in comparison to reading and overall academic achievement, there is evidence to suggest that ADHD is associated with greater difficulties in various aspects of writing (e.g., written expression, spelling, and dysgraphia), in comparison to other academic areas (Kroese et al., 2000; Mayes et al., 2000; Mayes & Calhoun, 2007). With respect to spelling in particular, children with ADHD make more errors on both dictation and copying tasks than children without ADHD (Re & Cornoldi, 2013). The difficulties with spelling have been suggested to be related to self-regulatory problems rather than orthographic weaknesses (Re et al., 2008). More specifically, spelling accuracy has been linked to inattention (Noda et al., 2013) and working memory deficits (Re et al., 2014) whereas copying accuracy has been linked to fine motor ability (Noda et al., 2013). In the present study, spelling was measured with the WIAT. For the WIAT spelling subtest, participants are asked to write down words dictated by the examiner. Thus, it is possible that errors made were reflective of problems with inattention (Noda et al., 2013). As previously discussed, although inattentive symptoms did not significantly differ among the two ADHD groups, the ADHD No Post-Secondary group did have higher mean symptom levels than the ADHD Post-Secondary group. Thus, it is possible that the different pattern of spelling achievement was related to the severity of inattentive symptoms.

Overall, with the exception of the change in spelling, there were no significant differences in the change in academic achievement across the four groups. This was to be

expected, because academic achievement is a relatively stable construct over time (Chen et al., 2014; Kowaleski-Jones & Duncan, 1999; Wright, 2010). Across the three measures, academic achievement was lowest for the ADHD No Post-Secondary group, who scored below the normative mean of 100 and highest for the LNCG Post-Secondary group, who scored above the normative mean. Both the ADHD Post-Secondary group and LNCG No Post-Secondary had scores that were roughly equivalent to the normative mean. Although the mean scores were higher for the ADHD Post-Secondary group than the LNCG No Post-Secondary, the scores were still lower than those of the LNCG Post-Secondary, suggesting that with respect to academic achievement there are differences among the two post-secondary groups. However, despite not catching up to their typically developing peers who attend post-secondary, the ADHD Post-Secondary group managed to gain admittance to post-secondary programs. Admittance to these programs is largely based on school performance. Thus, I turn to the results from the school performance trajectories.

School Performance

Mathematics School Performance

Table 5.7 shows the number of participants and the means and standard deviations for mathematics school grades from Grades 4-12. Figure 5.10 shows box plots of mathematics school grades for each grade. Figure 5.11 shows both the individual and average mathematics school grades for each grade, separated by group. Based on Figures 5.10 and 5.11, the slopes appeared to change from Grades 4-12, with a peak at Grade 8. Thus, in addition to a linear latent curve model, a piecewise latent curve model was tested with the knot at Grade 8 and model fit was compared. Furthermore, in Figure 5.11 it can be seen that all four groups experienced a steep decline in mathematics school grades as they transitioned from middle school to high school (i.e., Grades 8 to 9). This mean-level drop, labelled *transition*, was built into the model, equal for all four groups.

Likelihood ratio tests were performed to determine the optimal form of change between the unconditional linear model and the unconditional piecewise model. A Chi-square difference test showed that the piecewise function was better than the linear function, $\chi^2(4) = 19.31$, $p < .001$. The final piecewise model, which included the covariates, did not converge. Thus, the variance of the slope from Grades 8-12 was set to zero in the final model. The model had good fit, $\chi^2(132) = 155.96$, $p = .076$, SRMR = .066, CFI = .975, RMSEA = .019 [.000, .029]. See Table 5.8 for a summary of the unstandardized and standardized model results. See Figure 5.12 for the implied trajectories for the four groups.

Table 5.7

Means and Standard Deviations for Mathematics School Performance in Each Grade, Separated by Group

	Grade in School								
	4	5	6	7	8	9	10	11	12
ADHD Post-Secondary									
N	--	6	58	141	221	323	320	295	239
Mean	--	3.31	2.89	2.85	2.71	2.99	3.04	2.96	2.80
SD	--	1.89	1.09	1.24	1.16	1.33	1.30	1.27	1.15
ADHD No Post-Secondary									
N	1	10	47	92	107	166	129	90	61
Mean	3.67	2.25	2.67	2.67	2.76	2.41	2.40	2.74	2.65
SD	NA	0.96	1.11	1.30	1.26	1.32	1.13	1.06	1.17
LNCG Post-Secondary									
N	--	20	76	126	175	218	219	210	170
Mean	--	4.03	4.06	3.86	3.73	3.54	3.29	3.29	3.56
SD	--	0.92	0.83	1.12	1.06	1.08	1.16	1.26	1.09
LNCG No Post-Secondary									
N	--	8	27	37	45	56	51	39	25
Mean	--	3.33	2.68	2.78	2.93	2.54	2.61	2.7	2.55
SD	--	0.82	0.89	1.17	1.34	1.31	1.16	1.23	1.26

Note. Grades range from 1 (F) to 5 (A).

Figure 5.10

Box Plots and Scatterplots Showing Mathematics School Grades by Grade

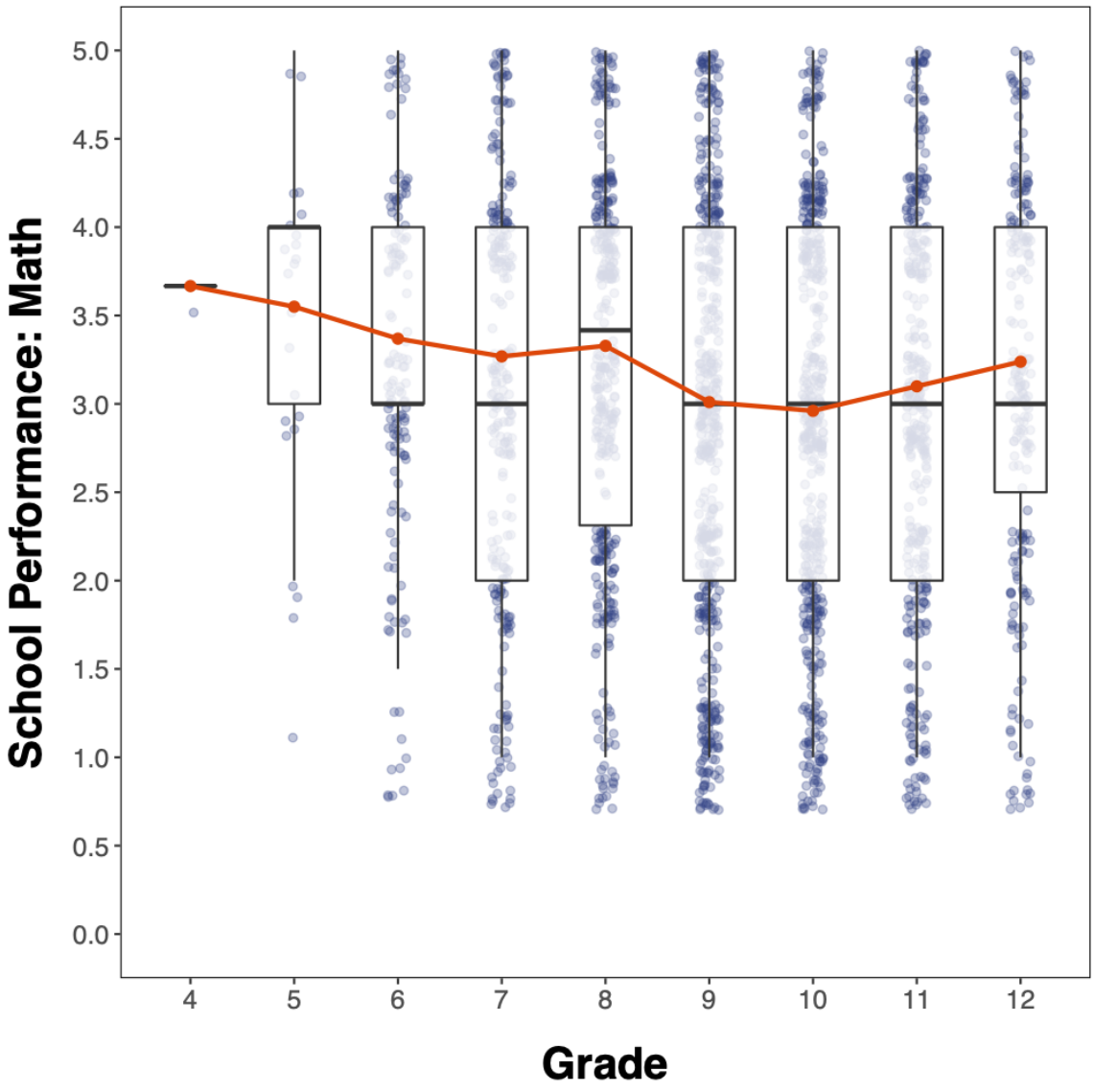


Figure 5.11

Individual and Mean Scores for Mathematics School Grades by Grade and Group

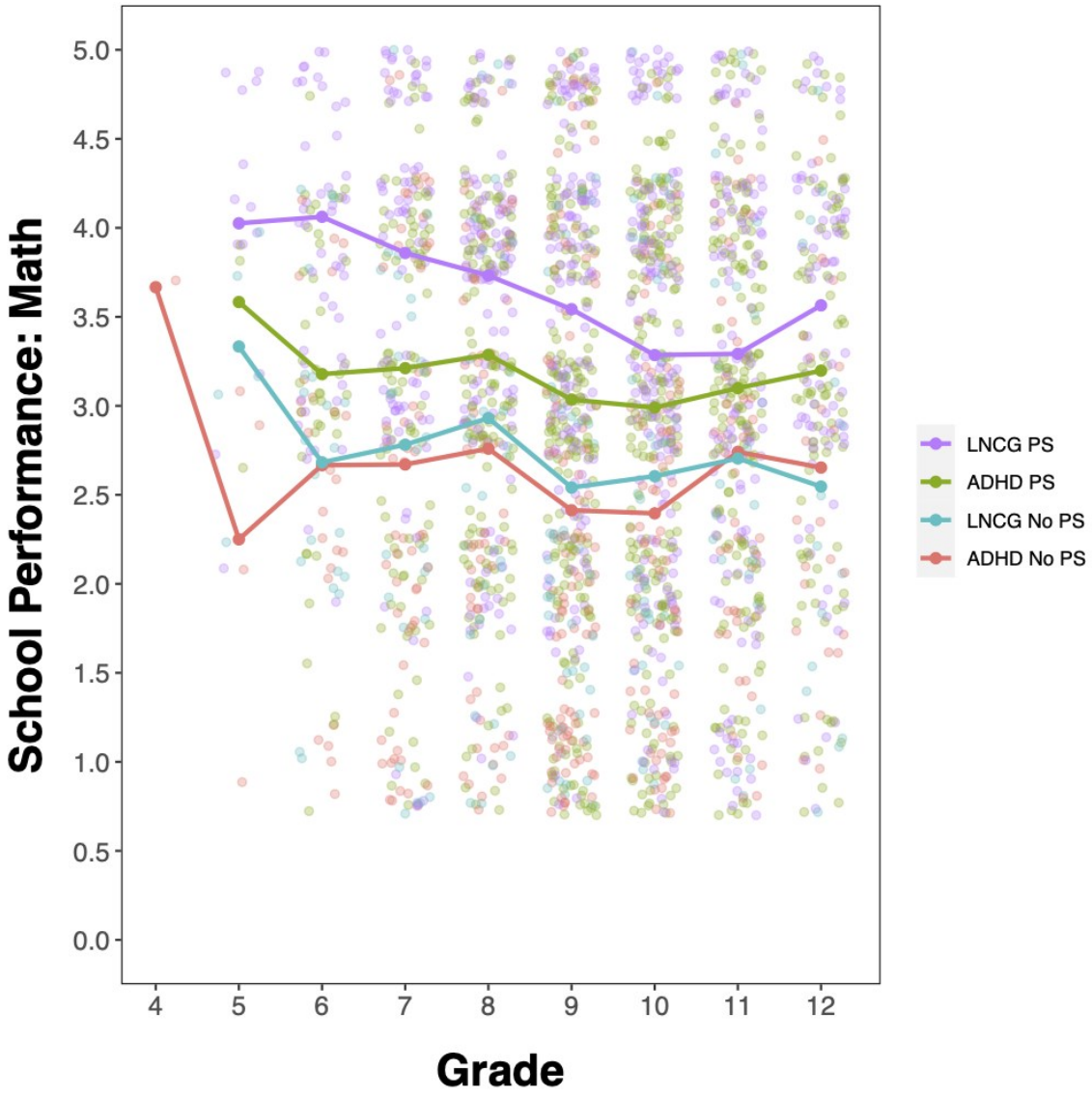


Table 5.8

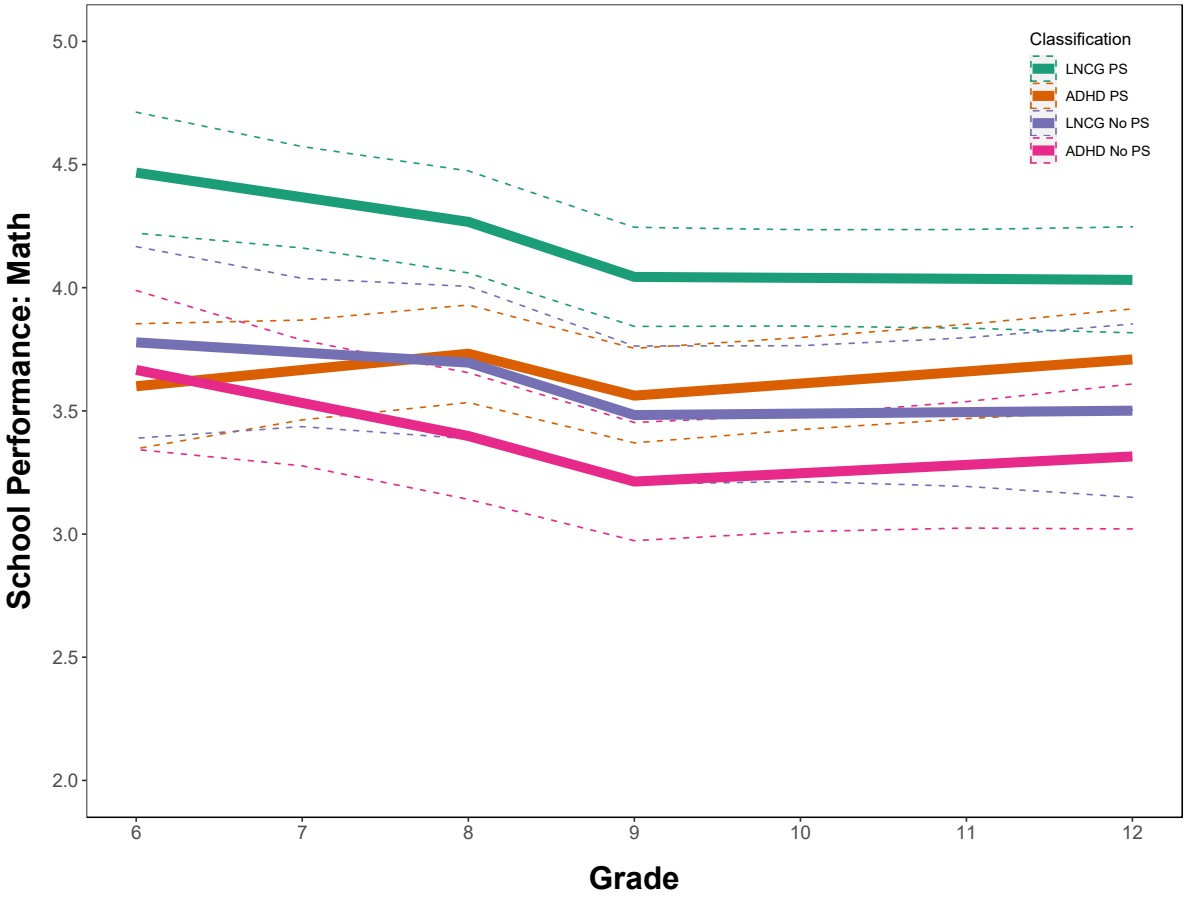
Mathematics School Grades Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	3.696*	0.189	4.315*	0.298
ADHD	-0.298	0.182	-0.169	0.103
Post-Secondary	0.571*	0.171	0.294*	0.087
ADHD*Post-Secondary	-0.237	0.206	-0.137	0.119
Rate of Change (Slope Gr. 6-8)	-0.041	0.111	-0.467	1.284
ADHD	-0.093	0.139	-0.519	0.741
Post-Secondary	-0.059	0.124	-0.301	0.622
ADHD*Post-Secondary	0.259*	0.162	1.477*	0.681
Transition (Gr. 8-9)	-0.219*	0.061	-0.558*	0.281
Rate of Change (Slope Gr. 9-12)	0.006	0.057	0.044	0.424
ADHD	0.028	0.071	0.100	0.256
Post-Secondary	-0.010	0.062	-0.033	0.201
ADHD*Post-Secondary	0.025	0.078	0.093	0.288
Covariates				
Sex (Male)	-0.143	0.081	-0.067	0.038
Treatment Site 2	-0.151	0.119	-0.061	0.048
Treatment Site 3	-0.110	0.134	-0.046	0.056
Treatment Site 4	0.032	0.111	0.014	0.050
Treatment Site 5	0.082	0.110	0.037	0.050
Treatment Site 6	-0.612*	0.110	-0.273*	0.049
Ethnicity: Black	-0.317*	0.110	-0.131*	0.046
Ethnicity: Hispanic	-0.122	0.135	-0.043	0.047
Ethnicity: Other	-0.046	0.124	-0.015	0.040
Advantaged	-0.332*	0.073	-0.192*	0.042
Low-Income Status	0.116	0.162	0.031	0.043
Externalizing Disorder	-0.057	0.082	-0.028	0.041
Age of Mom at Birth	0.006	0.006	0.039	0.042
Social Assistance Income	-0.038	0.111	-0.015	0.044
Medication Management	0.021	0.084	0.010	0.039
Multimodal Superiority	0.031	0.060	0.020	0.039
Behavioural Substitution	-0.047	0.060	-0.030	0.039

*$p < .05$

Figure 5.12

Implied Trajectories for Mathematics School Grades by Grade and Group with 90% Confidence Bands



Overall, eventual post-secondary enrolment was associated with mathematics school grades in Grade 8; adolescents who eventually enrolled in post-secondary studies had better mathematics grades than those who did not eventually enrol. ADHD histories did not significantly predict mathematics school grades in Grade 8. The ADHD by Post-Secondary interaction shows that the rate of change in mathematics school grades from Grades 6-8 differed among those with ADHD histories. Neither ADHD nor post-secondary enrolment were significantly associated with the rate of change in mathematics school grades from Grades 9-12. All groups experienced a decline in mathematics grades during the transition from middle to high school. After the transition, grades were relatively stable.

The pattern in Figure 5.12 shows that across all grades the LNCG Post-Secondary had the highest mathematics school grades. In middle school (i.e., Grades 6 to 8), the ADHD Post-Secondary group and LNCG No Post-Secondary had similar mathematics school grades. The ADHD No Post-Secondary group had the lowest mathematics school grades in middle school. The pattern of the slopes was different for the two ADHD histories groups in middle school. More specifically, the mathematics grades of the ADHD No Post-Secondary group declined whereas the grades of the ADHD Post-Secondary group slightly improved. In high school (i.e., Grades 9-12), mathematics grades remained relatively stable for all four groups. The trajectories in general were quite flat, with the exception of the transition to high school (i.e., Grade 8-9). In high school, the LNCG Post-Secondary consistently achieved the highest mathematics grades. The ADHD No Post-Secondary group consistently achieved the lowest mathematics grades, although the confidence bands overlap with the ADHD Post-Secondary group and

LNCG No Post-Secondary. Overall, post-secondary enrolment was associated with mathematics school grades in Grade 8, with a significant difference in the rates of change from Grades 6 to 8 for the ADHD Post-Secondary group in comparison to the ADHD No Post-Secondary group.

English School Performance

Table 5.9 shows the number of participants and the means and standard deviations for English school grades from Grades 4-12. Figure 5.13 shows box plots of English school grades for each grade. Figure 5.14 shows both the individual and average English school grades for each grade, separated by group. Based on Figures 5.13 and 5.14, the slopes appeared to change from Grades 4-12, with a peak at Grade 8. Thus, in addition to a linear latent curve model, a piecewise latent curve model was tested with the knot at Grade 8 and model fit was compared. Furthermore, in Figure 5.14 it can be seen that all four groups experienced a steep decline in English school grades as they transitioned from middle school to high school (i.e., Grades 8 to 9). This mean-level drop, labelled *transition*, was built into the model, equal for all four groups.

Likelihood ratio tests were performed to determine the optimal form of change between the unconditional linear model and the unconditional piecewise model. A Chi-square difference test showed that the piecewise function was better than the linear function, $\chi^2(4) = 22.28$, $p < .001$. The final piecewise model, with the covariates, had good fit, $\chi^2(128) = 146.49$, $p = .126$, SRMR = .017, CFI = .977, RMSEA = .017 [.000, .028]. See Table 5.10 for a summary of the unstandardized and standardized model results. See Figure 5.15 for the implied trajectories for the four groups.

Table 5.9

Means and Standard Deviations for English School Performance in Each Grade, Separated by Group

	Grade in School								
	4	5	6	7	8	9	10	11	12
ADHD Post-Secondary									
N	--	6	58	141	221	323	320	295	239
Mean	--	3.17	3.20	3.17	3.27	3.07	3.15	3.15	3.39
SD	--	0.52	0.99	1.09	1.04	1.07	1.01	1.03	1.03
ADHD No Post-Secondary									
N	1	10	47	92	107	166	129	90	61
Mean	3	2.12	2.73	2.66	2.56	2.59	2.62	2.79	3.09
SD	NA	0.85	0.98	1.14	1.25	1.13	1.25	1.19	1.13
LNCG Post-Secondary									
N	--	20	76	126	175	218	219	210	170
Mean	--	4.22	4.04	3.93	3.91	3.48	3.56	3.58	3.78
SD	--	0.78	0.91	0.98	0.98	1.04	1.11	1.04	1.00
LNCG No Post-Secondary									
N	--	8	27	37	45	56	51	39	25
Mean	--	3.60	2.98	3.13	3.04	2.73	2.94	2.93	2.77
SD	--	0.79	0.87	0.89	1.16	1.16	1.18	1.17	0.98

Note. Grades range from 1 (F) to 5 (A)

Figure 5.13

Box Plots and Scatterplots Showing English School Grades by Grade

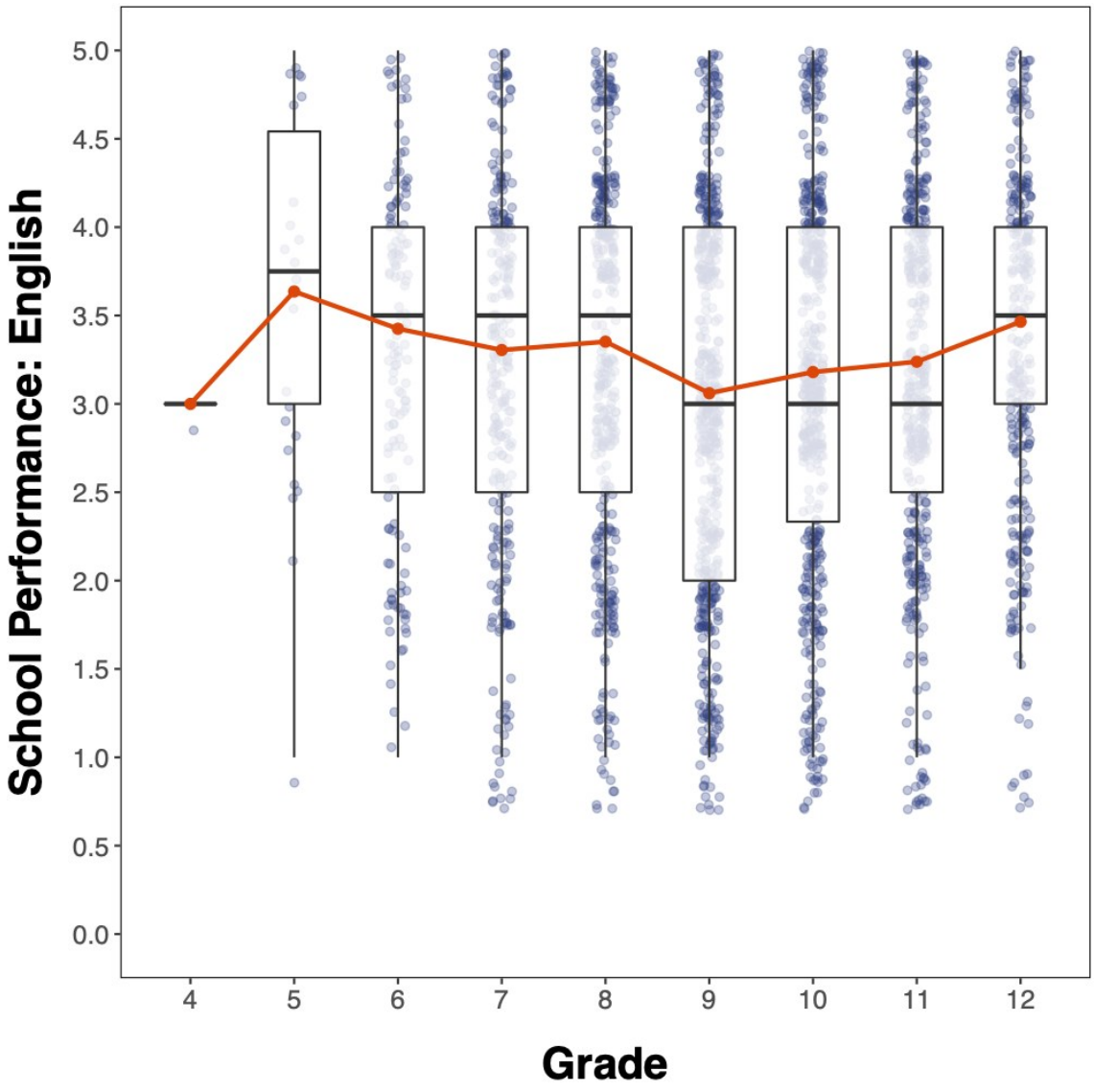


Figure 5.14

Individual and Mean Scores for English School Grades by Grade and Group

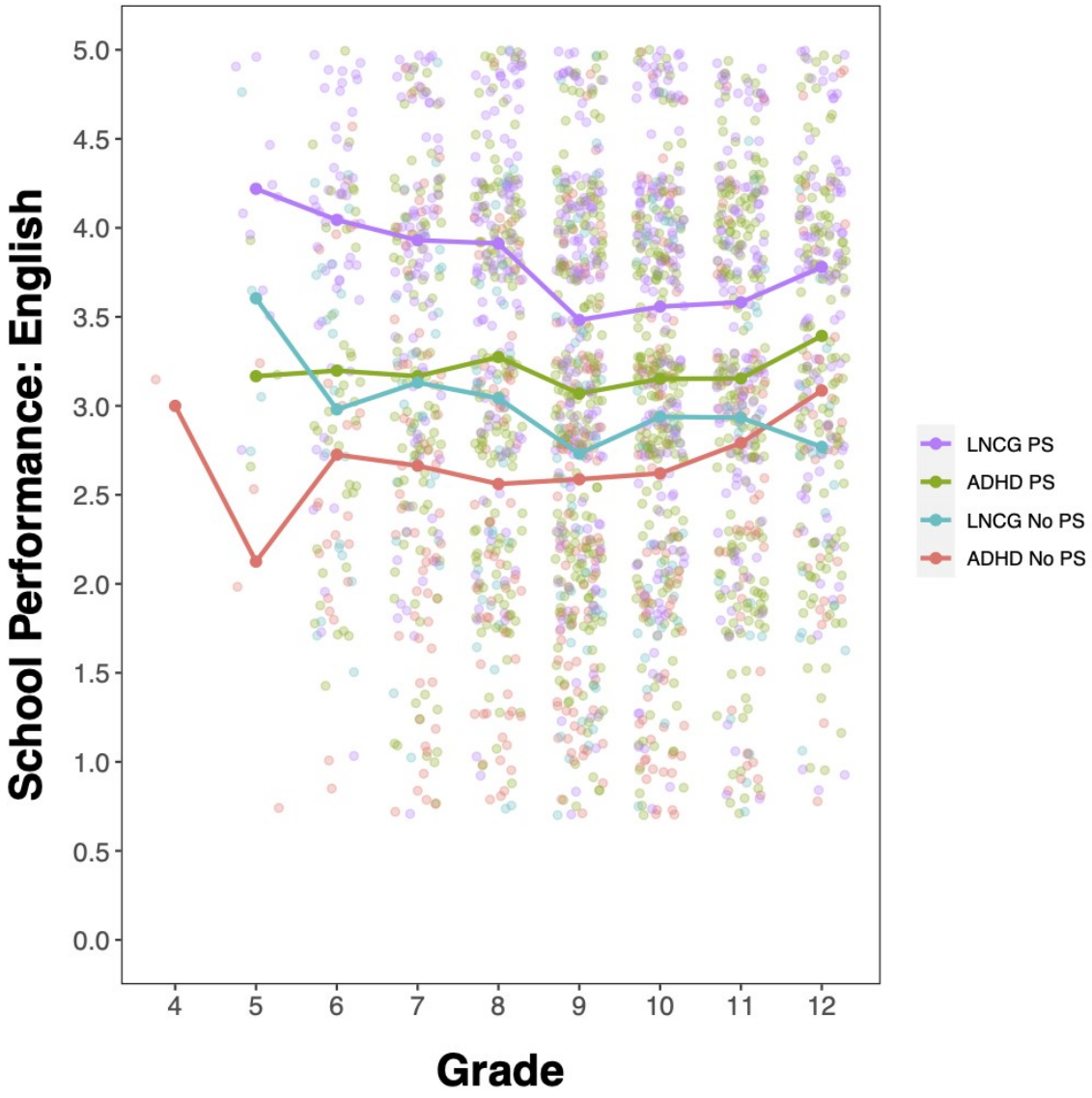


Table 5.10

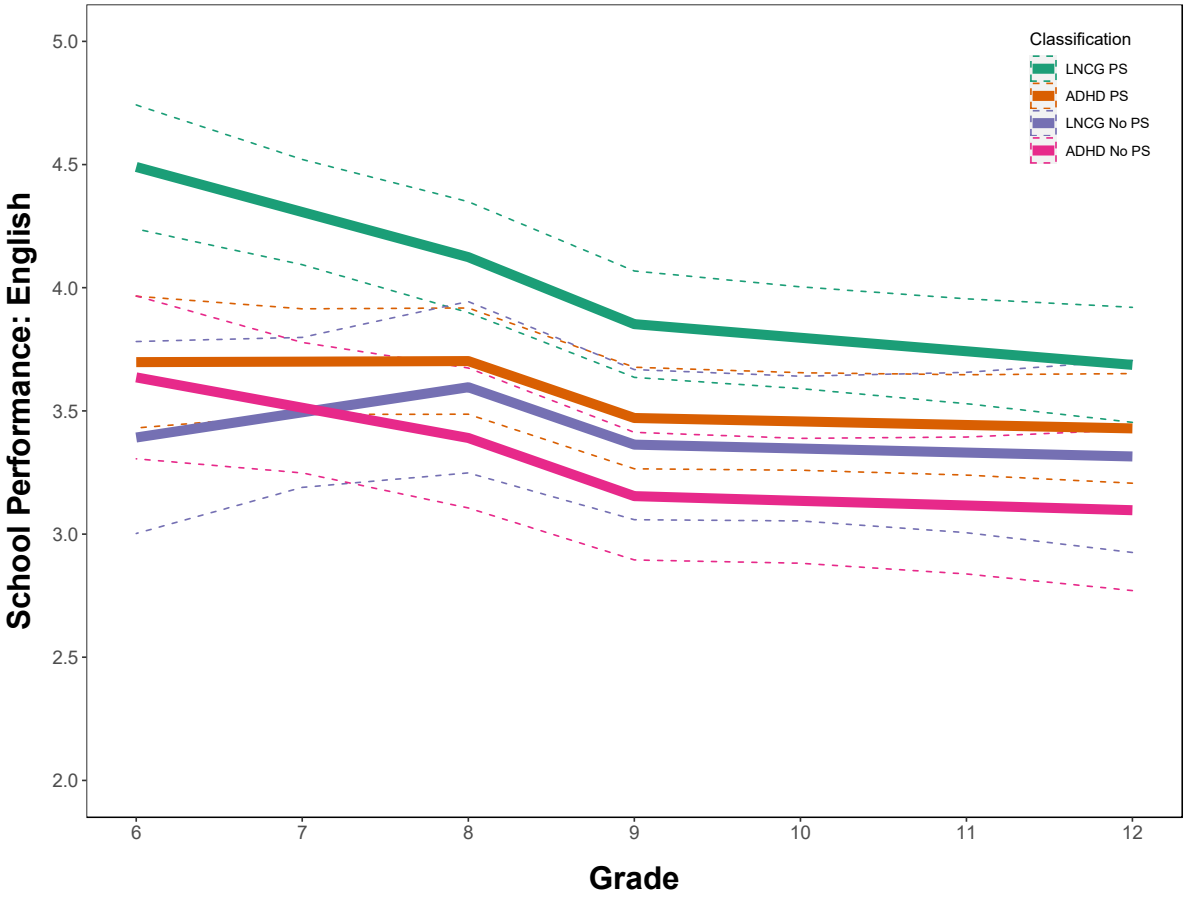
English School Grades Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	3.596*	0.212	3.499*	0.312
ADHD	-0.206	0.212	-0.097	0.100
Post-Secondary	0.528*	0.197	0.227*	0.085
ADHD*Post-Secondary	-0.216	0.238	-0.104	0.115
Rate of Change (Slope Gr. 6-8)	0.102	0.127	0.197	0.245
ADHD	-0.225	0.158	-0.211	0.149
Post-Secondary	-0.285*	0.142	-0.243*	0.123
ADHD*Post-Secondary	0.410*	0.183	0.391*	0.180
Transition (Gr. 8-9)	-0.217*	0.071	-0.322*	0.132
Rate of Change (Slope Gr. 8-12)	-0.016	0.070	-0.074	0.319
ADHD	0.003	0.085	0.006	0.188
Post-Secondary	-0.039	0.074	-0.079	0.151
ADHD*Post-Secondary	0.044	0.094	0.098	0.214
Covariates				
Sex (Male)	-0.097	0.085	-0.038	0.033
Treatment Site 2	-0.282*	0.127	-0.095*	0.043
Treatment Site 3	-0.005	0.142	-0.002	0.049
Treatment Site 4	0.049	0.117	0.018	0.044
Treatment Site 5	0.107	0.117	0.041	0.044
Treatment Site 6	-0.649*	0.117	-0.242*	0.047
Ethnicity: Black	-0.337*	0.116	-0.116*	0.04
Ethnicity: Hispanic	-0.231	0.143	-0.068	0.042
Ethnicity: Other	0.036	0.127	0.010	0.035
Advantaged	-0.378*	0.076	-0.182*	0.038
Low-Income Status	-0.050	0.167	-0.011	0.038
Externalizing Disorder	-0.059	0.087	-0.024	0.036
Age of Mom at Birth	0.009	0.006	0.051	0.037
Social Assistance Income	0.047	0.117	0.016	0.039
Medication Management	-0.021	0.089	-0.008	0.034
Multimodal Superiority	0.064	0.063	0.035	0.034
Behavioural Substitution	0.019	0.064	0.010	0.034

*$p < .05$

Figure 5.15

Implied Trajectories for English School Grades by Grade and Group with 90% Confidence Bands



Overall, eventual post-secondary enrolment was associated with English school grades in Grade 8; adolescents who eventually enrolled in post-secondary studies had better English grades than those who did not eventually enrol. ADHD histories did not significantly predict English school grades in Grade 8. Both post-secondary enrolment and the interaction between ADHD histories and post-secondary enrolment was significantly associated with the rate of change in English school grades from Grades 6-8. From Grades 9-12, neither ADHD histories nor eventual post-secondary enrolment were significantly associated with the rate of change in English school grades. Thus, there were mean-level group differences in English grades for those who did versus did not eventually enrol in post-secondary studies. For adolescents with ADHD histories, English grades of the ADHD No Post-Secondary group declined more than the ADHD Post-Secondary group during middle school (i.e., Grades 6-8) but the grades did not change differently in high school (i.e., Grades 9-12). The LNCG did not change differently over time in either middle or high school. All groups experienced a decrease in English grades during the transition from middle to high school (i.e., Grades 8-9). After the transition, grades were relatively stable.

The pattern in Figure 5.15 shows that, in general, the LNCG Post-Secondary had the highest English school grades from Grades 6 to 12, although this difference was only significant in middle school. In Grade 8, the ADHD Post-Secondary group and LNCG No Post-Secondary had similar English grades; the ADHD No Post-Secondary group had the lowest English grades. From Grades 6-8, the trajectories were different for the four groups. For the LNCG Post-Secondary and the ADHD No Post-Secondary group, English grades declined in middle school. For the LNCG No Post-Secondary, English

grades improved in middle school. For the ADHD Post-Secondary group, English grades were stable in middle school. In high school, the four groups had similar trajectories, with all four groups having relatively stable English grades from Grades 9-12. All four groups experienced a decline in English grades during the transition from middle to high school. Overall, post-secondary enrolment was associated with English school grades in Grade 8. From Figure 5.15, it is evident that the LNCG Post-Secondary is driving the effect of post-secondary enrolment on English school grades. The rates of change across the four groups differed in Grades 6-8, with adolescents with ADHD histories who did not eventually enrol in post-secondary studies experiencing a steeper decline in English grades than those who did eventually enrol. The rates of change from Grades 9-12 across the four groups were not significantly different.

School Performance: Grade Point Average

Table 5.11 shows the number of participants and the means and standard deviations for Grade Point Averages (GPAs) from Grades 4-12. Figure 5.16 shows box plots of GPAs for each grade. Figure 5.17 shows both the individual and average GPAs for each grade, separated by group. Based on Figures 5.16 and 5.17, the slopes appeared to change from Grades 4-12, with a peak at Grade 8. Thus, in addition to a linear latent curve model, a piecewise latent curve model was tested with the knot at Grade 8 and model fit was compared. Furthermore, in Figure 5.17 it can be seen that all four groups experienced a steep decline GPA as they transitioned from middle school to high school (i.e., Grade 8-9). This mean-level drop, labelled *transition*, was built into the model, equal for all four groups.

Likelihood ratio tests were performed to determine the optimal form of change between the unconditional linear model and the unconditional piecewise model. A Chi-square difference test showed that the piecewise function was better than the linear function, $\chi^2(4) = 29.77$, $p < .001$. The final piecewise model with the covariates had acceptable fit, $\chi^2(128) = 199.35$, $p < .001$, SRMR = .043, CFI = .973, RMSEA = .029 [.021, .037]. See Table 5.12 for a summary of the unstandardized and standardized model results. See Figure 5.18 for the implied trajectories for the four groups.

Table 5.11

Means and Standard Deviations for Grade Point Average in Each Grade, Separated by Group

	Grade in School								
	4	5	6	7	8	9	10	11	12
ADHD Post-Secondary									
N	--	6	58	141	221	323	320	295	239
Mean	--	2.45	2.45	2.42	2.42	2.23	2.30	2.35	2.60
SD	--	0.47	0.73	0.77	0.79	0.86	0.81	0.85	0.74
ADHD No Post-Secondary									
N	1	10	47	92	107	166	129	90	61
Mean	2.83	1.98	1.98	1.77	1.82	1.55	1.62	1.81	2.00
SD	NA	0.76	0.76	0.89	0.90	0.97	0.93	0.97	1.08
LNCG Post-Secondary									
N	--	20	76	126	175	218	219	210	170
Mean	--	2.92	3.13	3.10	3.13	2.82	2.79	2.79	2.87
SD	--	0.78	0.74	0.76	0.78	0.88	0.88	0.88	0.85
LNCG No Post-Secondary									
N	1	8	27	37	45	56	51	39	25
Mean	2.00	2.44	2.28	2.11	2.03	1.72	1.80	2.02	1.79
SD	NA	0.42	0.76	0.77	0.85	0.95	0.87	0.85	0.92

Note. GPA scale ranges from 0 to 4 with higher GPA indicating better school performance.

Figure 5.16

Box Plots and Scatterplots Showing Grade Point Averages by Grade

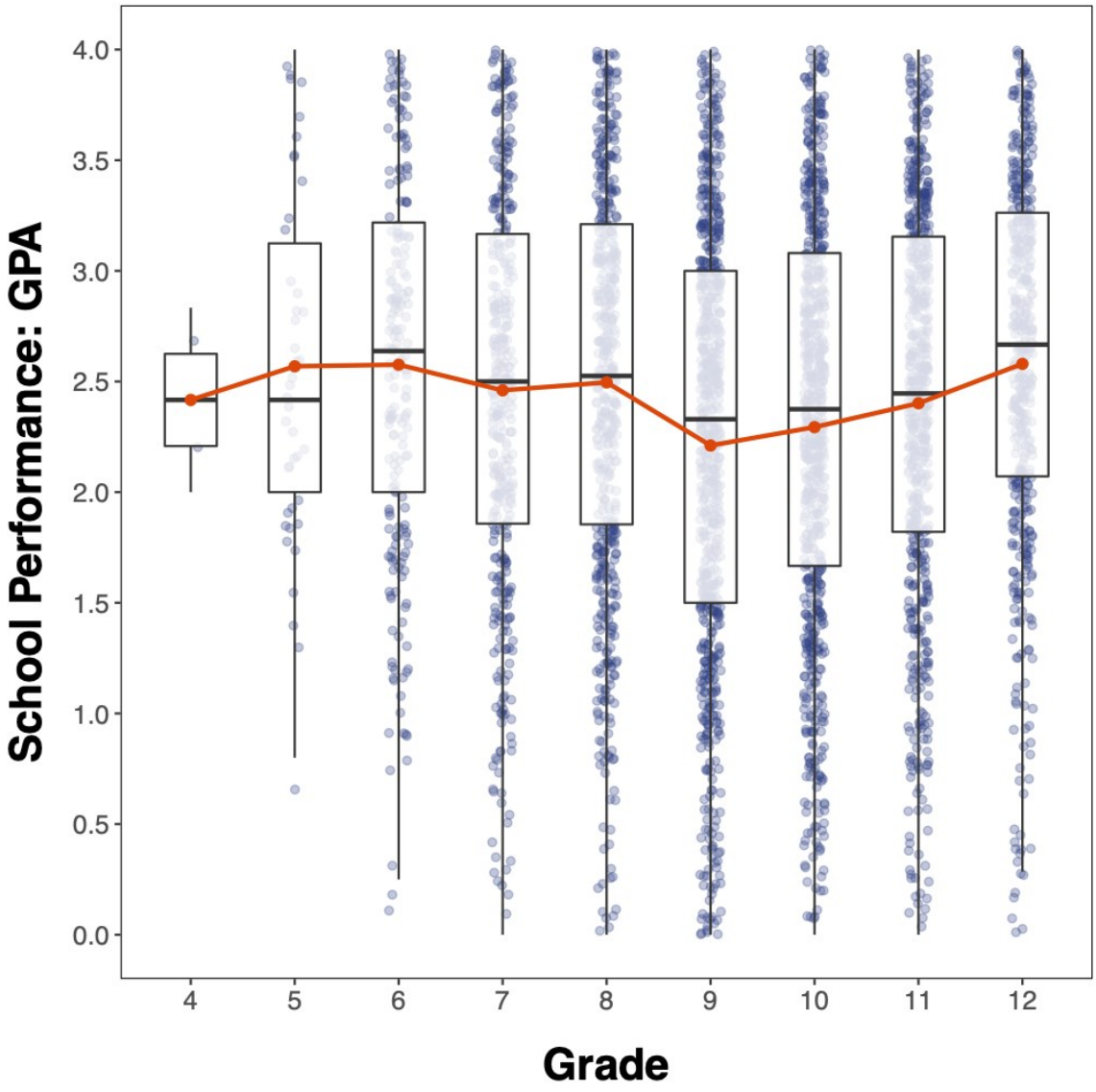


Figure 5.17

Individual and Mean Scores for Grade Point Averages by Grade and Group

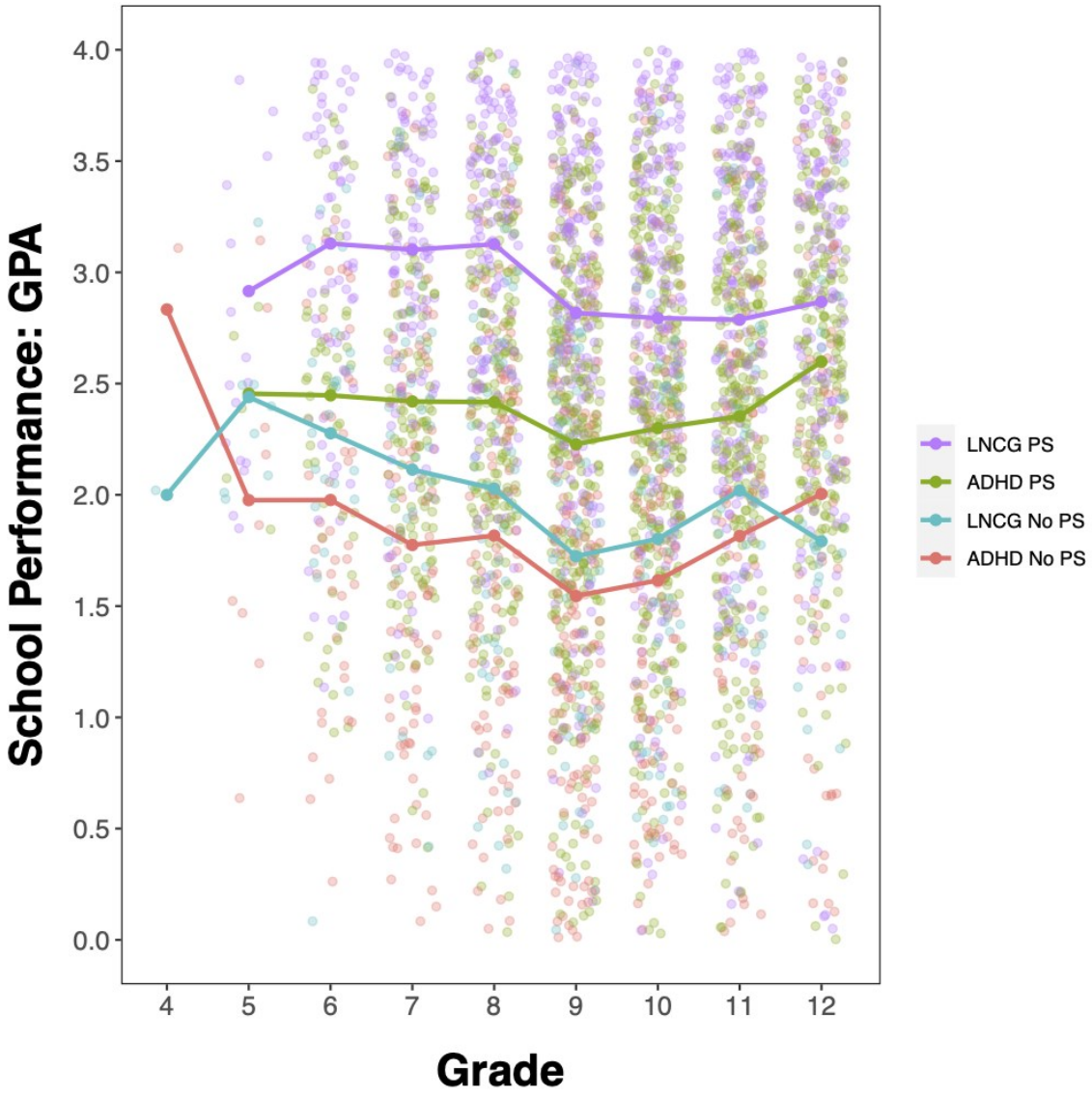


Table 5.12

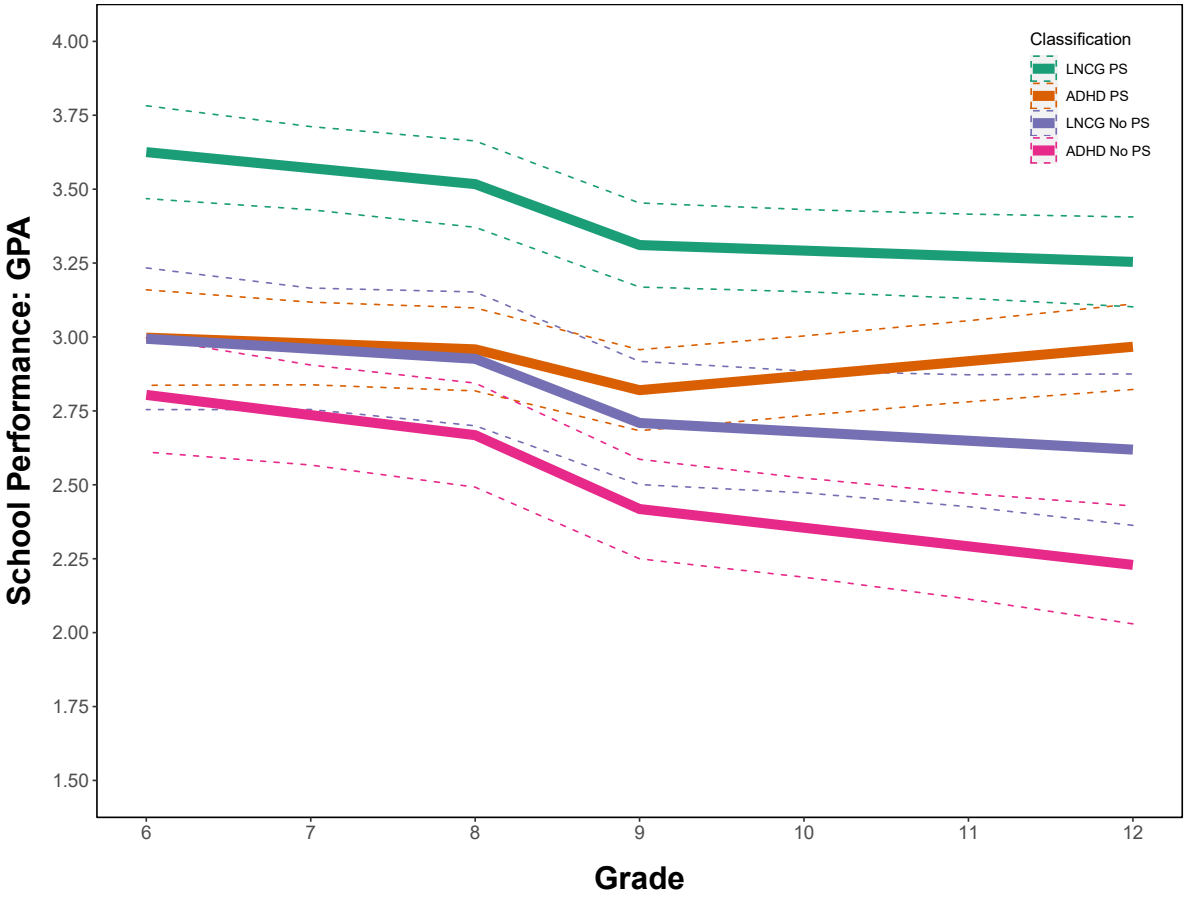
Grade Point Averages Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	2.926*	0.138	3.361*	0.200
ADHD	-0.257	0.134	-0.142	0.073
Post-Secondary	0.584*	0.129	0.302*	0.065
ADHD*Post-Secondary	-0.306*	0.151	-0.172*	0.085
Rate of Change (Slope Gr. 6-8)	-0.034	0.067	-0.167	0.339
ADHD	-0.034	0.081	-0.080	0.196
Post-Secondary	-0.020	0.075	-0.045	0.167
ADHD*Post-Secondary	0.068	0.094	0.167	0.240
Transition (Gr. 8-9)	-0.187*	0.035	-0.338*	0.072
Rate of Change (Slope Gr. 8-12)	-0.030	0.449	-0.147	0.194
ADHD	-0.033	0.046	-0.077	0.109
Post-Secondary	0.011	0.042	0.025	0.092
ADHD*Post-Secondary	0.101*	0.051	0.246*	0.125
Covariates				
Sex (Male)	-0.170*	0.057	-0.080*	0.027
Treatment Site 2	-0.104	0.086	-0.041	0.034
Treatment Site 3	-0.414*	0.095	-0.170*	0.039
Treatment Site 4	-0.076	0.079	-0.034	0.035
Treatment Site 5	-0.009	0.079	-0.004	0.035
Treatment Site 6	-0.594*	0.08	-0.257*	0.036
Ethnicity: Black	-0.322*	0.076	-0.136*	0.032
Ethnicity: Hispanic	-0.049	0.099	-0.016	0.033
Ethnicity: Other	-0.026	0.086	-0.009	0.028
Advantaged	-0.339*	0.052	-0.192*	0.030
Low-Income Status	-0.009	0.111	-0.003	0.031
Externalizing Disorder	-0.037	0.058	-0.018	0.029
Age of Mom at Birth	0.011*	0.004	0.074*	0.029
Social Assistance Income	-0.047	0.078	-0.019	0.032
Medication Management	-0.122*	0.059	-0.056*	0.027
Multimodal Superiority	-0.009	0.042	-0.006	0.027
Behavioural Substitution	-0.039	0.042	-0.025	0.027

*$p < .05$

Figure 5.18

Implied Trajectories for Grade Point Averages by Grade and Group with 90% Confidence Bands



Overall, eventual post-secondary enrolment was associated with school GPA in Grade 8; ADHD histories were marginally associated with school GPA in Grade 8 (p = .052). The ADHD histories post-secondary interaction was also associated with GPA in Grade 8. In comparing within groups, adolescents with ADHD histories who eventually enrolled in post-secondary studies had higher GPAs in Grade 8 than those who did not eventually enrol. Within the LNCG, adolescents who eventually enrolled in post-secondary studies had higher GPAs in Grade 8 than those who did not eventually enrol. From Grades 6-8 neither ADHD histories nor eventual post-secondary enrolment were significantly associated with the rate of change in GPA. From Grades 8-9, all four groups experienced a decline in GPA as they transitioned from middle to high school. From Grades 9-12, the interaction between ADHD histories and post-secondary enrolment was associated with the rate of change in GPA.

The pattern in Figure 5.18 shows that, from Grades 6-12 the LNCG had the highest GPA. In Grade 8, the ADHD Post-Secondary group and LNCG No Post-Secondary had similar GPAs. Furthermore, from Grades 6-8 all four groups had similar slopes – the trajectories were relatively flat across these three grades. For the LNCG, the trajectories were similar for those who did and did not enrol in post-secondary studies from Grades 8-12, with relatively stable GPAs over time. Interestingly, the ADHD Post-Secondary and ADHD No Post-Secondary groups had very different slopes from Grades 9-12. For the ADHD No Post-Secondary group, GPA declined over time. In contrast, for the ADHD Post-Secondary group, GPA improved. Overall, in both middle school and high school the LNCG Post-Secondary had higher GPAs than the other three groups. Of most interest though are the trajectories for adolescents with ADHD histories. In middle

school, the ADHD histories groups had similar slopes, both experiencing a slight decline in GPA from Grades 6-8. From Grades 9-12, however, the GPAs of the ADHD Post-Secondary group improved, almost catching up to the LNCG Post-Secondary by Grade 12, whereas the GPAs of the ADHD No Post-Secondary group declined. Thus, it seems that the differences in school performance between these two groups was most evident in high school.

Discussion: School Performance

To try and closely mirror the standardized academic achievement assessments from the WIAT, mathematics, and English school performance trajectories were analyzed. Additionally, to examine overall school performance, grade point average (GPA) developmental trajectories were analyzed from Grades 6-12. Unlike academic achievement, and contrary to my prediction, ADHD histories were not associated with mathematics or English school performance in Grade 8: Adolescents with ADHD histories did not have significantly worse mathematics or English grades than adolescents without ADHD histories. In contrast, as was predicted, post-secondary enrolment was related to grades in both subject areas. In examining the trajectories, it is evident that from Grade 6 onward, the LNCG Post-Secondary had better mathematics and English school grades than the other three groups. From Grades 6-8, the trajectories differed for the two ADHD groups, with the ADHD No Post-Secondary group experiencing a decline in both math and English grades in middle school. After the initial transition to high school where all four groups experienced a decline in grades, the trajectories became quite stable from Grades 9-12.

Similar to mathematics and English grades, in Grade 8 post-secondary enrolment was associated with overall GPA; ADHD was only marginally associated with GPA. Additionally, there was a significant ADHD by post-secondary enrolment interaction. In Grade 8 the ADHD Post-Secondary group had higher GPAs than the ADHD No Post-Secondary group. Although this result is consistent with my prediction that the ADHD Post-Secondary group would have better school performance because they may be functioning similarly to their non-ADHD peers (Loe & Feldman, 2007), as predicted, they did not have equivalent performance to the LNCG Post-Secondary. In the literature, students with ADHD histories continue to face academic challenges, even in post-secondary education, compared to their typically developing peers (Lewandowski et al., 2008). Accordingly, in the present study, by Grade 8 the ADHD Post-Secondary group had similar GPAs to their typically developing peers who did not eventually enrol in post-secondary studies (i.e., LNCG No Post-Secondary), but they continued to achieve lower academic performance than their typically developing peers who did eventually enrol (i.e., LNCG Post-Secondary).

Previous research has found that student grades tend to decline during transition periods, for example, as they move from middle to high school (Alspaugh, 1998; Barber & Olsen, 2004). Thus, for school performance I added a transition variable to account for the change in grades from Grade 8-9. For all four groups, students experienced a decline in mathematics and English grades and overall GPA when they transitioned to high school. Moreover, there was a significant ADHD by post-secondary interaction in middle school for both mathematics and English grades. The grades of the ADHD Post-Secondary group remained stable across middle school whereas the grades of the ADHD

No Post-Secondary group declined from Grades 6-8. Interestingly, at the beginning of middle school (i.e., Grade 6), the two ADHD groups had similar mathematics and English grades. However, by Grade 8 there is roughly half a letter grade difference in scores. Although the difference was not significant, teachers and parents reported greater inattentive symptom levels for the ADHD No Post-Secondary group than the ADHD Post-Secondary group during middle school (i.e., ages 11-14). Similarly, the ADHD No Post-Secondary group had lower reading and spelling academic achievement scores than the ADHD Post-Secondary group. Thus, this decline in English and mathematics grades may reflect persistent inattentive symptoms among the ADHD No Post-Secondary group (Hechtman et al., 2016), which may have negatively impacted school performance.

By high school, different patterns began to emerge. Contrary to what was predicted, there were no significant differences in rates of change for either English or mathematics among the four groups. In high school, English and mathematics grades remained relatively stable. The overall pattern was similar to academic achievement: The LNCG Post-Secondary continuously had the highest grades, the ADHD No Post-Secondary group had the lowest grades and the ADHD Post-Secondary group and LNCG No Post-Secondary had similar grades, falling in between the other two groups. However, an interesting pattern emerged with respect to overall GPA. In high school, there was an ADHD by post-secondary slope interaction. For the ADHD No Post-Secondary group, grades continued to decline at a similar rate to middle school, as evidenced by the similar slope for both middle and high school. In contrast, for the ADHD Post-Secondary group, GPA improved in high school. I elaborate on this finding in Chapter 8.

Discussion: Academic Outcomes

In the present study, two different measures of academic outcomes were used: standardized academic achievement (i.e., WIAT Mathematics, WIAT Reading, WIAT Spelling) and school performance (i.e., Math grades, English grades, GPA). With respect to mean differences across the groups, the patterns were similar. At the intercept (age 13 for academic achievement, Grade 8 for school performance) the LNCG Post-Secondary had the highest scores/grades and the ADHD No Post-Secondary group had the lowest scores/grades. The ADHD Post-Secondary group and LNCG No Post-Secondary had similar scores/grades.

The change over time, however, differed for academic achievement and school performance. For academic achievement, with the exception of WIAT spelling, the scores remained relatively stable over time, with each group experiencing a slight decline in academic achievement from ages 9-17. For WIAT spelling, the ADHD No Post-Secondary group had a steeper decline than the ADHD Post-Secondary group. For school performance, the trajectories differed in middle school from high school. The most noticeable difference was with respect to overall GPA: The ADHD Post-Secondary group GPA improved over time, whereas GPA for the ADHD No Post-Secondary group declined. For the LNCG, GPA remained relatively stable in high school. Interestingly, even though WIAT scores for the ADHD Post-Secondary group remained stable, their school performance nonetheless improved in high school. This suggests that there is more captured in overall GPA (i.e., a composite of all grades) than just fundamental knowledge of mathematics, reading, and spelling.

The general pattern for academic outcomes was that, with the exception of overall GPA, the ADHD Post-Secondary group and LNCG No Post-Secondary had similar mean scores and trajectories, whereas the LNCG Post-Secondary consistently had better academic outcomes and the ADHD No Post-Secondary group consistently had worse academic outcomes. Overall, school performance, measured by GPA, showed the most differential changes over time across the four groups.

CHAPTER 6: DEVELOPMENTAL TRAJECTORIES OF ANXIETY AND DEPRESSION SYMPTOMS

In this chapter the results of the latent curve modelling analyses for anxiety and depression symptoms are presented. The goal was to address the following questions: i) Do the trajectories of anxiety and depression symptoms differ for adolescents with or without ADHD histories who did or did not attend post-secondary? ii) Are there level differences in anxiety and depression when students transition from childhood to adolescence? iii) Is growth in anxiety related to growth in depression in adolescents with or without ADHD?

Anxiety Symptoms

Table 6.1 shows the number of participants and the means and standard deviations for mean anxiety symptoms from ages 8-18. Figure 6.1 shows box plots of mean anxiety symptoms at each age. Figure 6.2 shows both individual and average anxiety symptoms for each age, separated by group. Based on Figures 6.1 and 6.2, the slope did not appear to be linear for the four groups. Thus, in addition to a linear latent curve model, a piecewise latent curve model was tested with the knot at age 13 and a cubic model (i.e., a wave that decreases, increases, then decreases again) was tested with the intercept at 13; model fit was compared.

Table 6.1

Means and Standard Deviations for Anxiety Symptoms at Each Age, Separated by Group

	Age (in Years)										
	8	9	10	11	12	13	14	15	16	17	18
ADHD Post-Secondary											
N	--	115	157	185	103	84	124	129	173	130	23
Mean	--	2.29	2.23	2.13	2.11	2.03	1.91	1.94	1.92	1.87	1.90
SD	--	0.47	0.45	0.42	0.43	0.40	0.39	0.37	0.43	0.37	0.41
ADHD No Post-Secondary											
N	2	56	96	101	53	48	59	62	90	71	7
Mean	2.02	2.38	2.19	2.12	1.97	1.88	1.84	1.80	1.80	1.79	1.67
SD	0.66	0.50	0.43	0.45	0.42	0.41	0.46	0.42	0.410	0.40	0.26
LNCG Post-Secondary											
N	21	68	119	105	75	65	73	95	93	104	2
Mean	2.39	2.33	2.24	2.13	1.99	1.93	1.91	1.87	1.89	1.86	1.59
SD	0.36	0.41	0.37	0.36	0.30	0.36	0.36	0.34	0.39	0.36	0.14
LNCG No Post-Secondary											
N	10	15	28	20	17	17	17	19	23	17	--
Mean	2.51	2.35	2.30	2.05	1.90	2.03	1.98	1.95	1.80	1.87	--
SD	0.33	0.39	0.37	0.31	0.37	0.34	0.32	0.39	0.42	0.31	--

Figure 6.1

Box Plots and Scatterplots Showing Mean Anxiety Symptoms by Age

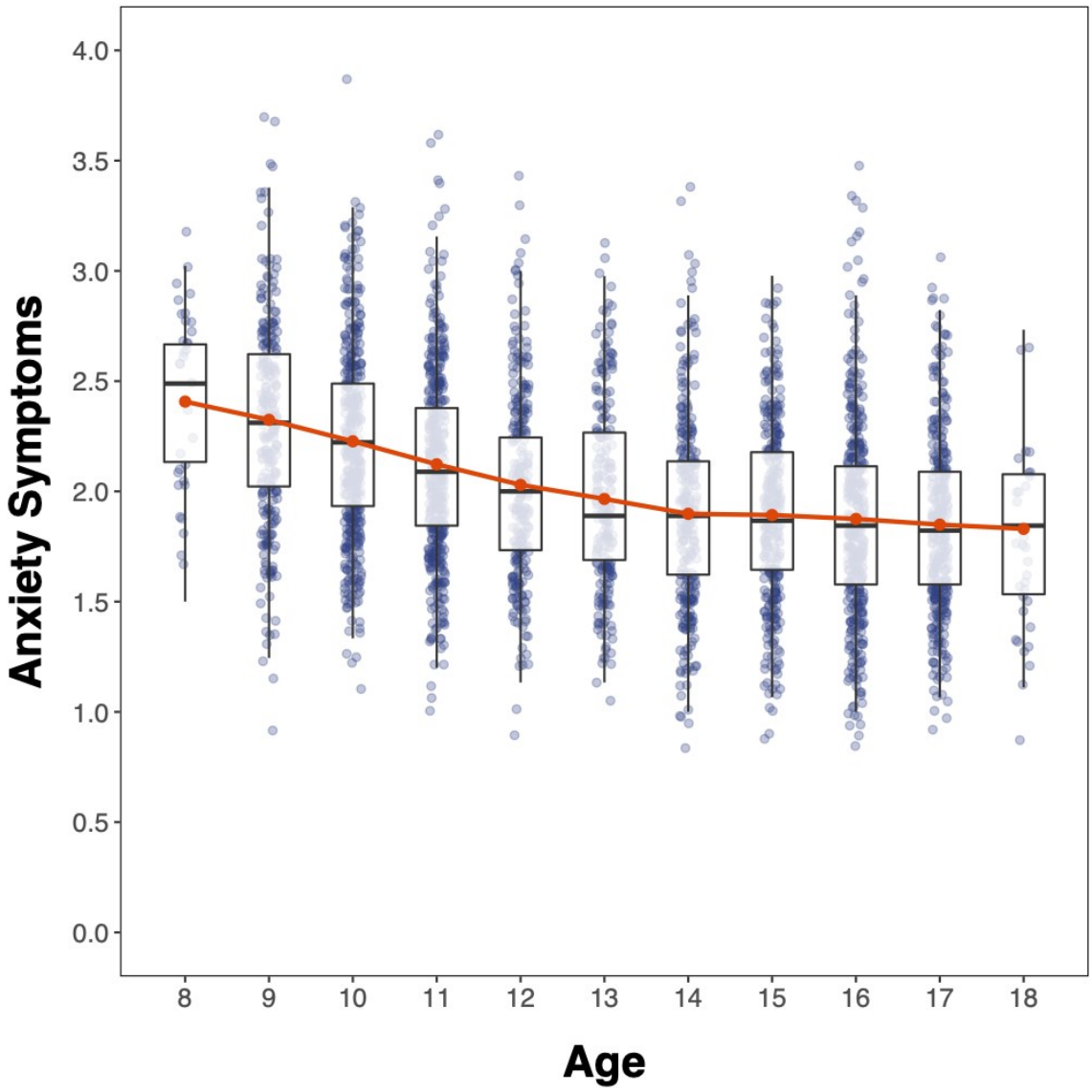
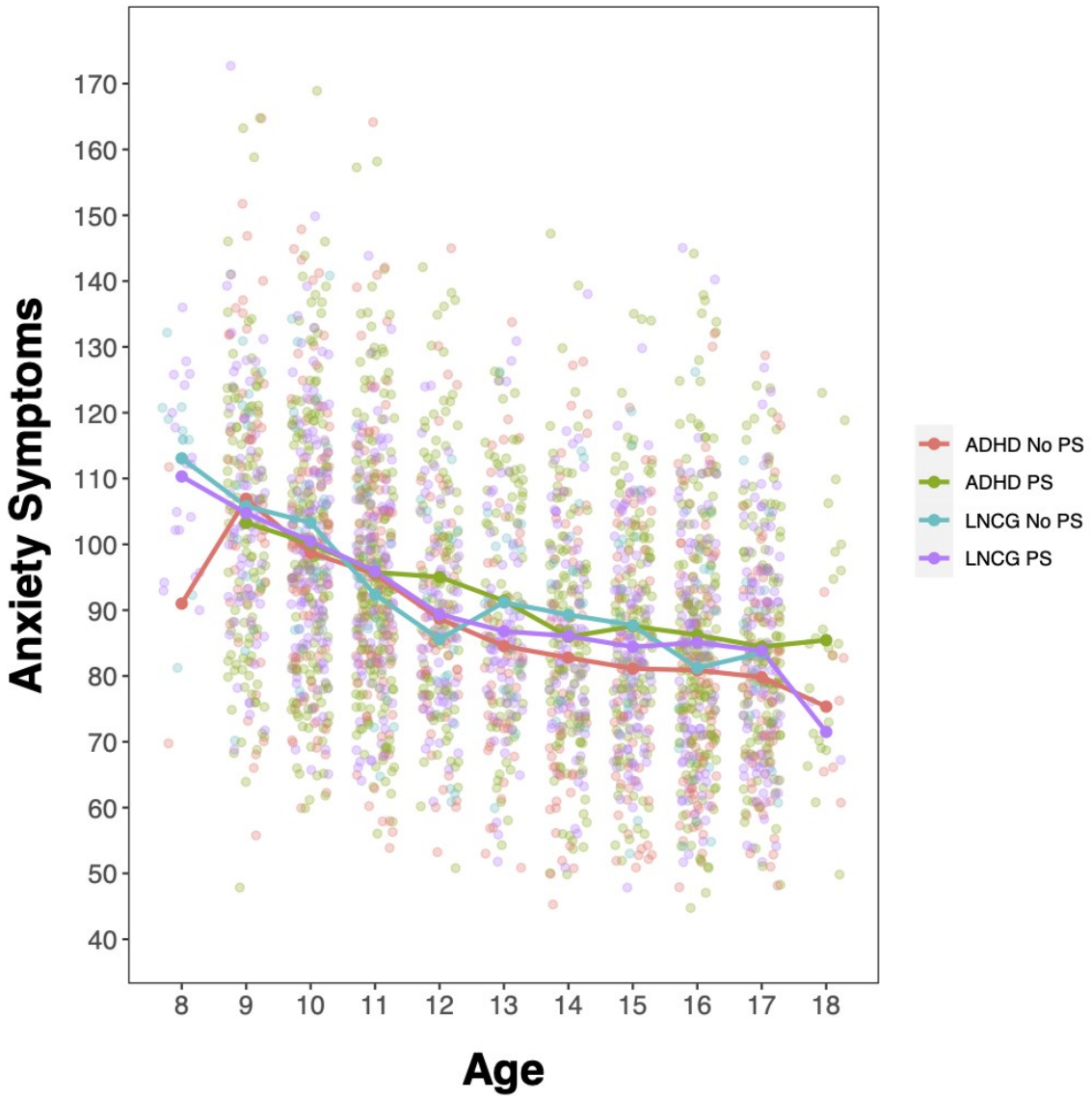


Figure 6.2

Individual and Mean Scores for Anxiety Symptoms by Age and Group



Likelihood ratio tests were performed to determine the optimal form of change between the unconditional linear model, the unconditional piecewise model, and the unconditional cubic model. Chi-square difference tests showed that both the piecewise function, $\chi^2(4) = 77.95$, $p < .001$, and cubic function, $\chi^2(9) = 84.67$, $p < .001$, were better than the linear function. A Chi-square difference test showed that the piecewise and cubic function did not significantly differ, $\chi^2(5) = 6.72$, $p = .243$.

Depression Symptoms

Table 6.2 shows the number of participants and the means and standard deviations for mean depression symptoms from ages 8-18. Figure 6.3 shows box plots of mean depression symptoms at each age. Figure 6.4 shows both individual and average depression symptoms for each age, separated by group. In general, depression symptoms were quite low from ages 8-18 for all four groups. Based on Figures 6.3 and 6.4, the slope did not appear to be linear for the four groups. Thus, in addition to a linear latent curve model, a piecewise latent curve model was tested with the knot at age 13 and a cubic model was tested with the intercept at 13; model fit was compared. Likelihood ratio tests were performed to determine the optimal form of change between the unconditional linear model, the unconditional piecewise model, and the unconditional cubic model. Chi-square difference tests showed that the cubic function was better than both the linear function, $\chi^2(9) = 42.14$, $p < .001$, and piecewise function, $\chi^2(5) = 45.75$, $p < .001$.

Table 6.2

Means and Standard Deviations for Depression Symptoms at Each Age, Separated by Group

	Age (in Years)										
	8	9	10	11	12	13	14	15	16	17	18
ADHD Post-Secondary											
N	--	158	184	103	85	122	129	172	132	22	115
Mean	--	0.21	0.20	0.22	0.22	0.22	0.26	0.26	0.27	0.21	0.24
SD	--	0.24	0.21	0.22	0.21	0.25	0.24	0.28	0.27	0.18	0.26
ADHD No Post-Secondary											
N	2	57	96	100	52	48	59	61	90	71	7
Mean	0.35	0.25	0.21	0.23	0.22	0.22	0.21	0.26	0.28	0.25	0.19
SD	0.34	0.2	0.19	0.19	0.22	0.17	0.25	0.26	0.29	0.26	0.22
LNCG Post-Secondary											
N	21	68	119	105	74	66	71	96	93	103	--
Mean	0.29	0.20	0.18	0.14	0.13	0.13	0.17	0.19	0.22	0.17	--
SD	0.33	0.19	0.18	0.15	0.14	0.17	0.24	0.23	0.28	0.20	--
LNCG No Post-Secondary											
N	10	15	28	20	17	17	17	18	24	17	--
Mean	0.25	0.32	0.17	0.16	0.16	0.26	0.25	0.27	0.26	0.23	--
SD	0.24	0.24	0.15	0.12	0.18	0.23	0.25	0.22	0.30	0.18	--

Figure 6.3

Box Plots and Scatterplots Showing Mean Depression Symptoms by Age

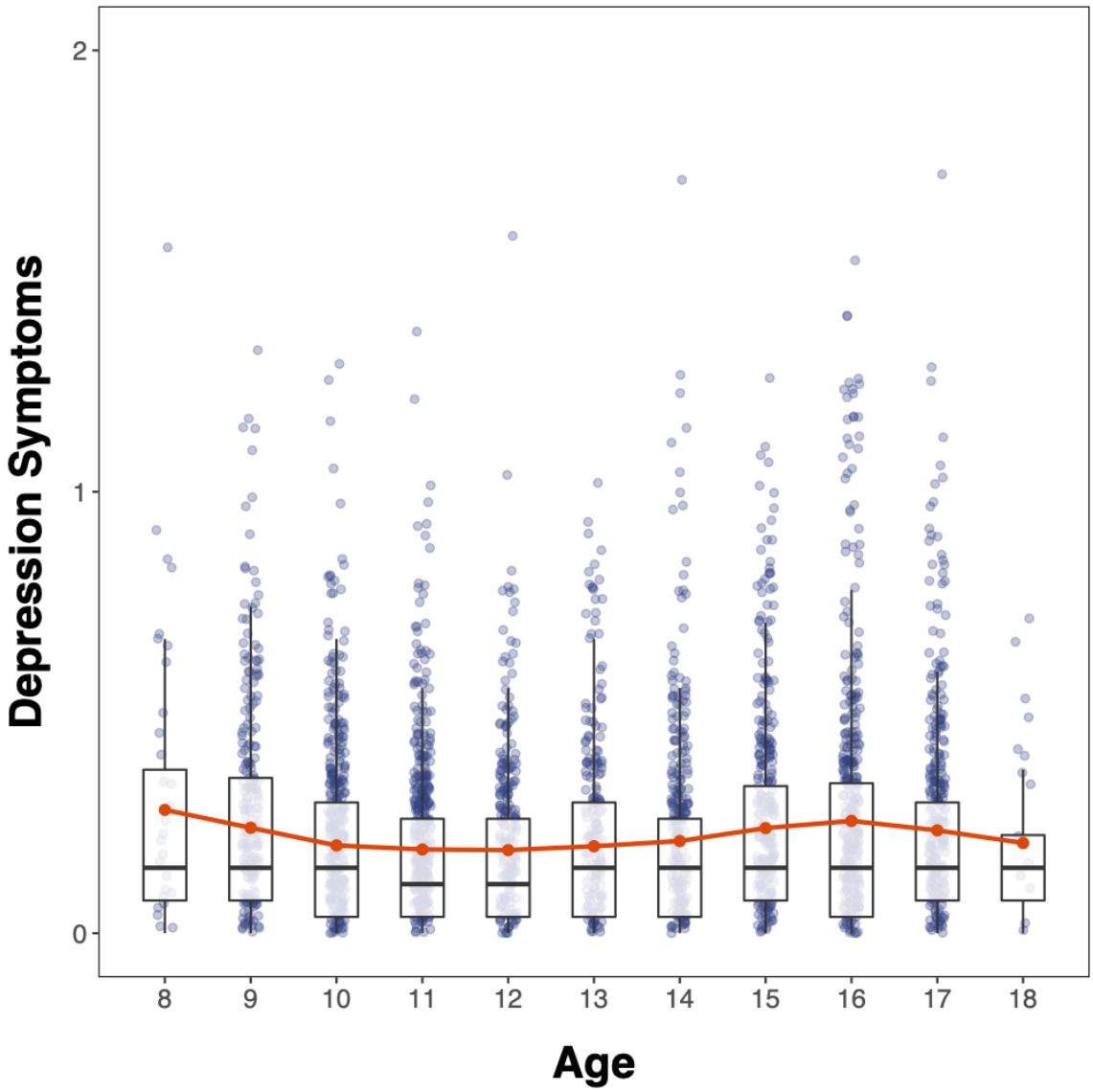
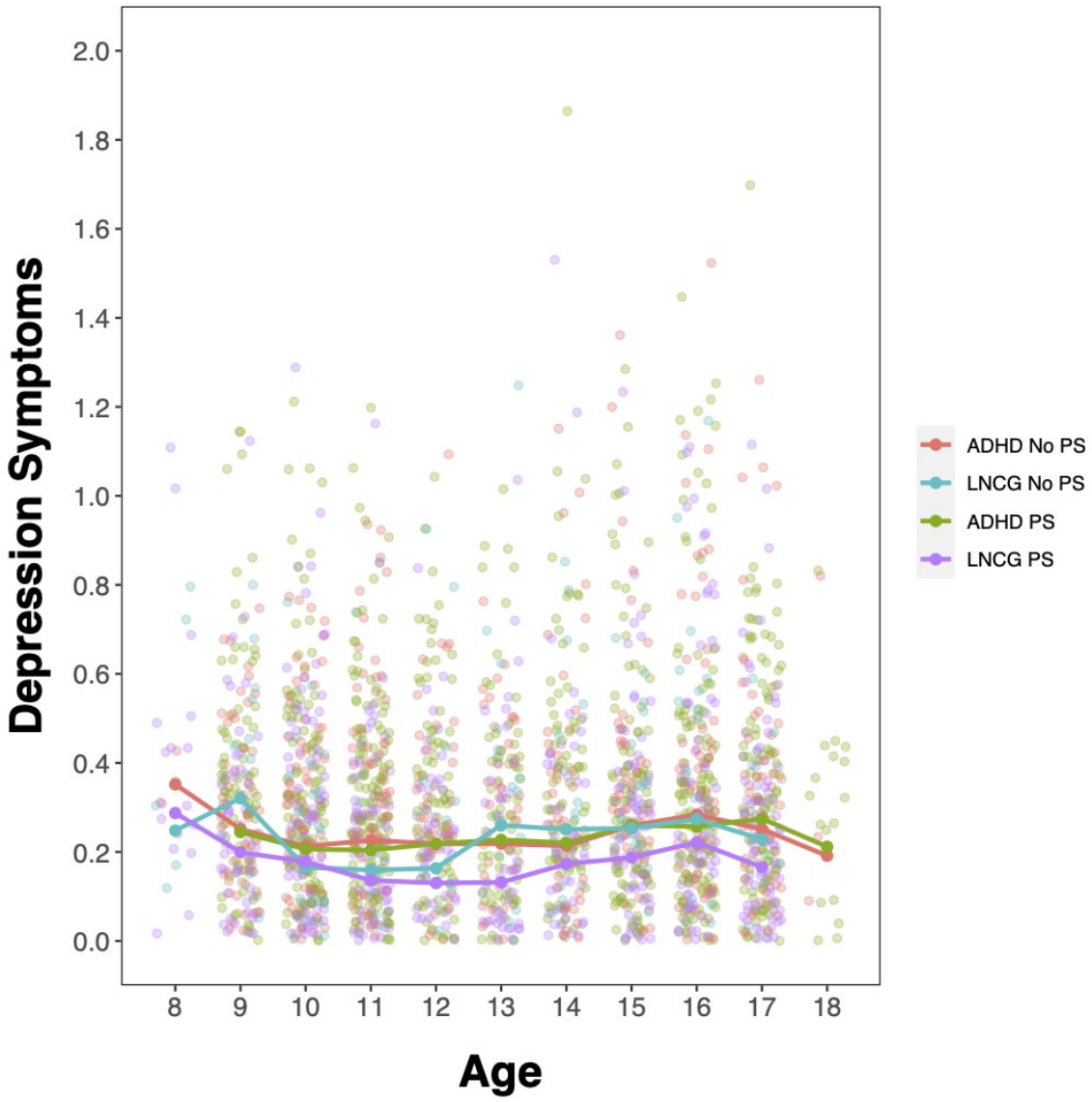


Figure 6.4

Individual and Mean Scores for Depression Symptoms by Age and Group



Parallel Model for Anxiety and Depression Symptoms

A latent curve model for two parallel processes (i.e., anxiety symptoms and depression symptoms) was tested. First, the model was tested specifying piecewise anxiety and cubic depression functions, but the model had poor fit. Next, the model was tested specifying cubic functions for both anxiety and depression. There were issues with convergence so the variance for the quadratic and cubic slopes were set to zero. The final model had acceptable fit, $\chi^2(458) = 663.33$, $p < .001$, SRMR = .072, CFI = .872, RMSEA = .025 [.021, .029]. See Tables 6.3, 6.4, and 6.5 for summaries of the unstandardized and standardized model results. See Figure 6.5 for the implied anxiety and depression trajectories for the four groups.

Table 6.3

Anxiety Symptoms Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	2.000*	0.058	7.475*	0.334
ADHD	-0.021	0.050	-0.037	0.088
Post-Secondary	0.001	0.050	0.002	0.085
ADHD*Post-Secondary	0.044	0.056	0.081	0.104
Rate of Change (Slope Age 9-17)				
Linear	-0.061*	0.013	-1.152*	0.246
Quadratic	0.009*	0.001	--	--
Cubic	-0.001	0.000	--	--
ADHD	-0.005	0.013	-0.041	0.116
Post-Secondary	0.007	0.013	0.062	0.109
ADHD*Post-Secondary	0.009	0.015	0.088	0.138
Covariates				
Sex (Male)	-0.146*	0.027	-0.219*	0.040
Treatment Site 2	0.061*	0.020	0.165*	0.054
Treatment Site 3	0.041*	0.015	0.168*	0.060
Treatment Site 4	0.031*	0.010	0.181*	0.055
Treatment Site 5	0.012	0.008	0.085	0.054
Treatment Site 6	0.011	0.006	0.091	0.054
Ethnicity: Black	0.064	0.035	0.088	0.048
Ethnicity: Hispanic	0.033	0.045	0.037	0.050
Ethnicity: Other	0.047	0.038	0.052	0.043
Advantaged	-0.017	0.025	-0.032	0.045
Low-Income Status	-0.045	0.051	-0.043	0.048
Externalizing Disorder	-0.022	0.027	-0.035	0.043
Age of Mom at Birth	-0.002	0.002	-0.054	0.045
Social Assistance Income	-0.015	0.036	-0.020	0.049
Medication Management	0.001	0.027	0.001	0.041
Multimodal Superiority	0.043*	0.019	0.094*	0.041
Behavioural Substitution	-0.019	0.019	-0.040	0.041

*$p < .05$

Table 6.4

Depression Symptoms Latent Curve Model Unstandardized and Standardized Results

	Unstandardized		Standardized	
	B	SE	β	SE
Intercept (age 13)	0.176*	0.030	1.339*	0.234
ADHD	0.010	0.025	0.035	0.092
Post-Secondary	-0.039	0.025	-0.135	0.088
ADHD*Post-Secondary	0.043	0.029	0.161	0.108
Rate of Change (Slope Age 9-17)				
Linear	0.019*	0.008	0.642*	0.253
Quadratic	0.003*	0.001	--	--
Cubic	-0.001*	0.000	--	--
ADHD	-0.002	0.008	-0.031	0.123
Post-Secondary	-0.004	0.008	-0.062	0.115
ADHD*Post-Secondary	0.006	0.009	0.099	0.145
Covariates				
Sex (Male)	-0.036*	0.014	-0.111*	0.042
Treatment Site 2	0.039*	0.010	0.217*	0.056
Treatment Site 3	0.017*	0.007	0.142*	0.062
Treatment Site 4	0.013*	0.005	0.157*	0.057
Treatment Site 5	0.002	0.004	0.033	0.056
Treatment Site 6	0.009*	0.003	0.149*	0.056
Ethnicity: Black	0.026	0.018	0.074	0.050
Ethnicity: Hispanic	0.039	0.023	0.087	0.051
Ethnicity: Other	0.010	0.019	0.022	0.044
Advantaged	-0.016	0.012	-0.059	0.047
Low-Income Status	-0.031	0.026	-0.061	0.050
Externalizing Disorder	0.061*	0.014	0.202*	0.044
Age of Mom at Birth	-0.001	0.001	-0.058	0.047
Social Assistance Income	0.019	0.018	0.052	0.050
Medication Management	-0.002	0.014	-0.005	0.043
Multimodal Superiority	0.018	0.010	0.080	0.043
Behavioural Substitution	-0.002	0.010	-0.008	0.042

*$p < .05$

Table 6.5

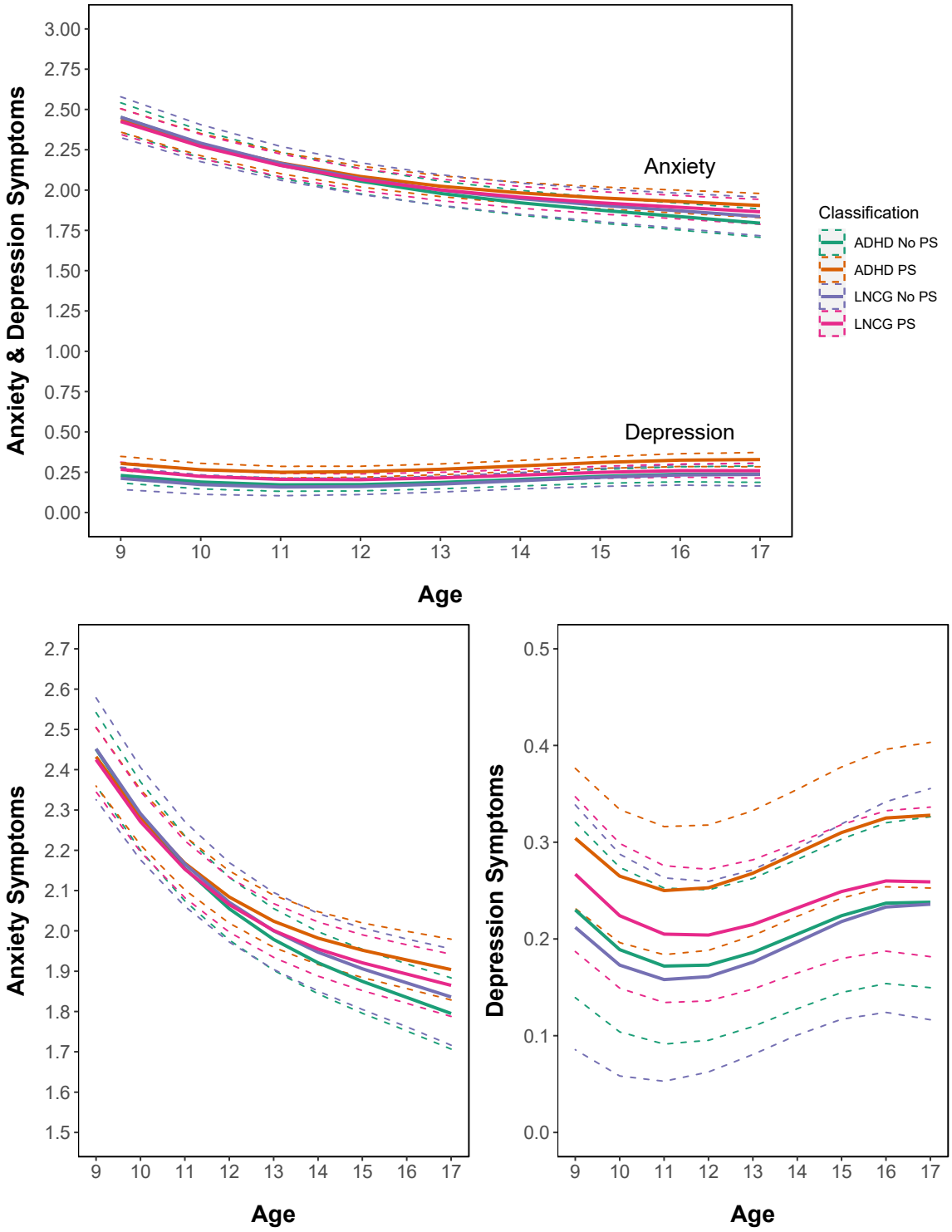
Anxiety and Depression Correlations at Each Age: Unstandardized and Standardized

	Unstandardized		Standardized	
	Estimate	SE	Estimate	SE
Anxiety with Depression				
Age 9	-0.002	0.005	-0.047	0.119
Age 10	0.006	0.003	0.150	0.084
Age 11	0.004	0.003	0.123	0.076
Age 12	0.006	0.003	0.170	0.089
Age 13	0.010*	0.004	0.256*	0.081
Age 14	0.007	0.004	0.127	0.073
Age 15	0.007	0.004	0.133	0.073
Age 16	0.017*	0.005	0.297*	0.073
Age 17	0.010*	0.004	0.270*	0.102

*$p < .05$

Figure 6.5

Implied Trajectories for Anxiety and Depression Symptoms by Age and Group with 90% Confidence Bands



A significant positive relationship was found between the intercept of anxiety symptoms and the intercept of depression symptoms (B = 0.015, SE = 0.002, $p < .001$; β = 0.507, SE = .044, $p < .001$). The slope-slope relationship was also significant (B = 0.001, SE = 0.000, $p < .001$; β = 0.440, SE = .079, $p < .001$). The trajectory of anxiety symptoms was related to the trajectory of depression symptoms: A steeper rate of change on anxiety symptoms was associated with a steeper rate of change on depression symptoms. Anxiety symptoms were rated on a 1 to 4 scale, whereas depression symptoms were rated on a 0 to 2 scale. Thus, the trajectories in Figure 5.18 are not directly comparable. However, based on the mean values, participants reported relatively low levels of anxiety (i.e., a rating of "2" on the MASC corresponds to "rarely true about me"). Similarly, participants reported very low levels of depressive symptoms from ages 9-17. In general, participants reported a slight decrease in anxiety symptoms over time whereas they reported stable, albeit very low, depression symptoms over time.

Neither ADHD nor eventual post-secondary enrolment were associated with anxiety or depression symptoms at age 13. Similarly, neither ADHD nor eventual post-secondary enrolment were associated with the change in symptoms over time (i.e., from ages 9 to 17). As can be seen in Figure 5.18, the trajectories were very similar for all four groups, both with respect to mean levels and slopes. The two post-secondary groups (i.e., ADHD Post-Secondary and LNCG Post-Secondary) reported slightly higher anxiety and depression symptoms in the teen years, but these values were not significantly different from their non-post-secondary peers (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary).

Discussion: Anxiety and Depression Symptoms

I examined the developmental trajectories of anxiety and depression, in parallel, from ages 9-17, considering the effects of ADHD histories and post-secondary enrolment. As was discussed in Chapter 2, there were many different possible trajectories to consider. First, it was possible that the groups who did not enrol in post-secondary studies (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary) would report higher mean levels of anxiety and depression and have steeper slopes than the post-secondary groups (i.e., ADHD Post-Secondary and LNCG Post-Secondary) because some of the literature states that anxiety and depression are negatively related to academic achievement (e.g., Beck, 1967; Duchesne et al., 2008; Hammen, 1998; Kirkaldy & Siefen, 1998; Singh & Thukral, 2009; Van Ameringen et al., 2003). Second, it was possible that adolescents with ADHD histories (i.e., ADHD Post-Secondary and ADHD No Post-Secondary) would report greater levels of anxiety and depression and have steeper slopes than the LNCG (i.e., LNCG Post-Secondary and LNCG No Post-Secondary) because both anxiety and depression are more prominent in adolescents with ADHD than among typically developing peers (Angold et al., 1999; Blase et al., 2009; MTA Cooperative Group, 1999b; Rabiner et al., 2008; Schatz & Rostain, 2006; Tannock, 2009). Third, it was possible that those who enrolled in post-secondary studies (i.e., ADHD Post-Secondary and LNCG Post-Secondary) would have higher levels of anxiety and depression than those who did not enrol (i.e., ADHD No Post-Secondary and LNCG No Post-Secondary) because some of the literature suggests that anxiety is not uncommon among gifted and high achieving students (Dammeyer & Nunez, 1999;

Dyrbye et al., 2006; Eisenberg et al., 2009; Evans et al., 2018; Guignard et al., 2012; Rotenstein et al., 2016; Suldo et al., 2018).

The results of the latent curve modelling did not support any of the three hypotheses. The mean reported levels of anxiety and depression and the rate of change were similar for all four groups. This is consistent with some of the literature which has found no differences between adolescents with and without ADHD on measures of anxiety and depression, and no significant relation between anxiety and depression and academic performance above and beyond a diagnosis of ADHD (Heiligenstein et al., 1999; Nelson & Gregg, 2012). ADHD symptoms may be so strongly associated with academic impairment that the co-occurrence of internalizing symptoms is unlikely to influence this relation (Becker et al., 2014; Biederman et al., 1996).

One possible explanation for the similar trajectories across the four groups is that anxiety and depression were measured using self-reports, as opposed to considering clinician diagnoses. Self-reports are not synonymous with diagnosis. In fact, the MASC and CDI are often used in clinical settings to gather data prior to an initial evaluation, not to make a diagnosis (March et al., 1997; Sitarenios & Kovacs, 1999). Correlations between the MASC and clinician ratings of anxiety are only moderate (Rynn et al., 2006).

Moreover, approximately 80% of the participants in the MTA were boys. Boys are more likely to under report symptoms of internalizing disorder than girls (Sigmon et al., 2005). Specific to the MASC, girls report higher anxiety symptoms across all subscales (March et al., 1997). Girls also had higher mean scores ($M = 2.38$) than boys ($M = 2.24$). In comparison to the boys sampled in March et al. (1997), in the present

sample the means were similar for ages 8-12, but were lower for ages 13-18, with mean scores across all four groups consistently falling below 2.00 (see Table 6.2). Specific to the CDI, in childhood boys reported higher depression symptoms than girls, but by adolescence girls reported higher depression symptoms than boys (Twenge & Nolen-Hoeksema, 2002). Longitudinally, girls had steady scores from ages 8-11, then scores increased from ages 12-16. In contrast, boys had stable scores from ages 8-16. This is consistent with the scores in the present study (see Table 6.2).

A previous study using the MTA data found that there was a high percentage of comorbid ADHD and anxiety among persons with ADHD histories even though their MASC scores fell within the normal range for both age and gender (March et al., 2000). Similarly, Hodges et al. (1990) compared CDI scores in children and adolescents with and without disruptive behaviour disorders and found no significant differences. Furthermore, a study examining the discriminant validity of the MASC found that the MASC was only moderately accurate (61%) at distinguishing children who received an anxiety disorder diagnosis from those who did not (Grills-Taquechel et al., 2008).

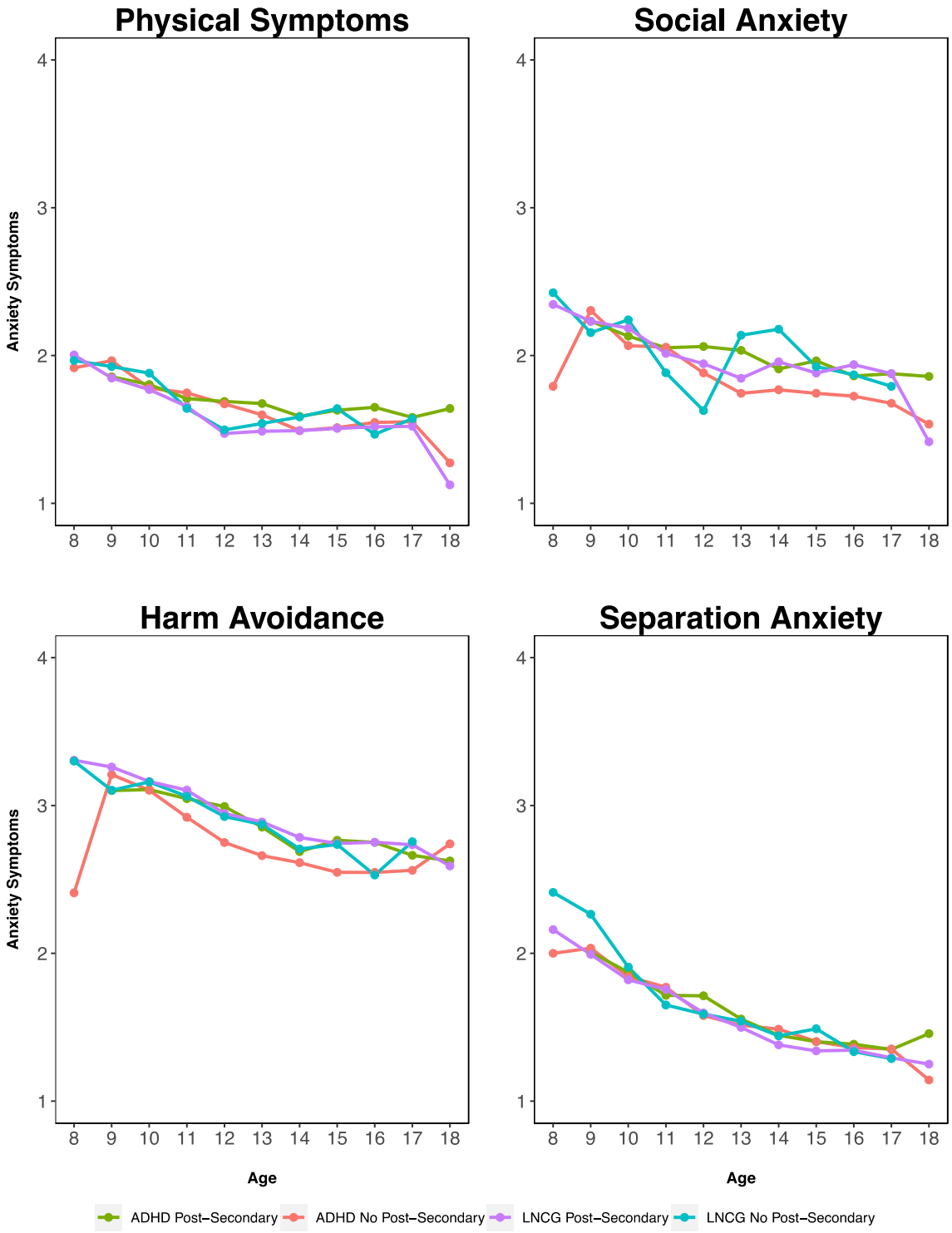
The comorbidity between ADHD and internalizing disorders is well known and cannot be attributed exclusively to factors such as methodological artifacts or referral biases (Angold et al., 1999). However, a second possibility is that persons who have ADHD and comorbid internalizing disorders may be a unique and separate class from those who have only ADHD. For example, MTA studies have found that treatment response qualitatively differed for children with ADHD alone versus those with ADHD and comorbid anxiety; enhanced responses were observed for children with comorbid disorders who received behavioural therapy (MTA Cooperative Group, 1999a, 1999b). In

general, children with comorbid anxiety, who made up approximately 33% of the ADHD histories group, tended to be more receptive to treatment than those with ADHD only (Jensen et al., 2001). Thus, to understand the trajectories of internalizing disorders, it may be necessary to consider comorbid groups separate from those with only ADHD.

Contrary to what was hypothesized, reported anxiety symptoms did not increase during adolescence for any of the four groups. Instead, reported symptoms declined slightly for all four groups. One possible explanation for this pattern is that average MASC scores were used, collapsing across subcategories, such as physical symptoms, harm avoidance, social anxiety, and separation/panic anxiety. Different subtypes of anxiety present at different ages and are more common at different ages. When combining the MASC subscales, the resulting score is a measure of generalized anxiety, a subtype of anxiety whose onset is typically between the ages of 25 and 53 (Kessler et al., 2007). In contrast, separation anxiety and phobias tend to occur much earlier, with onsets between the ages of 7 and 14. Thus, the decreasing trajectories for the four groups may represent a decline in symptoms associated with childhood anxiety disorders. In contrast, given that all participants in the current study were under 18 years of age, the symptoms of generalized anxiety may not have reached their peak. Supporting this point, the graph in Figure 6.6 shows the mean scores at each age for each of the four subfactors of the MASC. In this figure, it is evident that separation anxiety declined as children got older. There is also a slight decline in physical symptoms and harm avoidance, whereas social anxiety remains relatively stable. Nonetheless, similar to the findings from the latent curve modelling analysis, the plots suggest similar levels and patterns of anxiety for the four groups.

Figure 6.6

Mean Scores for the Anxiety Subfactors of the MASC by Age and Group



As I hypothesized the trajectories were relatively low and flat for depression for all four groups, although no significant increase in symptoms occurred during adolescence. The trajectories are consistent with previous findings in which males reported stable scores in childhood and adolescence (Twenge & Nolen-Hoeksema, 2002) and in which a high proportion of males (> 80%) reported symptom levels consistent with non-depression (Ehrenberg et al., 1990). However, this finding is inconsistent with the etiology of depressive disorders in which prevalence rates tend to increase from childhood to adolescence (Maughan et al., 2013). Previous research has found that scores on the CDI tend to decrease across ages when measured longitudinally, whereas scores increase when reported cross-sectionally (Twenge & Nolen-Hoeksema, 2002). This decrease tends to be steady and fairly gradual and is likely a measurement effect.

Considering anxiety and depression together, anxiety and depression often co-occur, with anxiety typically diagnosed prior to depression (Pollack, 2005; Wittchen et al., 2000). In the present study, anxiety and depression symptoms were significantly correlated in some of the adolescent years (e.g., ages 13, 16, and 17) but not during childhood (i.e., ages 9-12). In addition, the shapes of the trajectories for anxiety and depression were quite different. This finding aligns with the previous literature which has found low correlations between MASC and CDI scores (Kovacs, 1992; March et al., 1997; Olason et al., 2004). Similar to the different subtypes of anxiety, if anxiety and depression do in fact represent the same underlying psychopathology, as suggested by the transdiagnostic approach to mental illness (Dalgleish et al., 2020), the present research highlights the importance of considering separate trajectories for children and adolescents

as there are developmental distinctions between the two symptom profiles when measured through self-reports (Zahn-Waxler et al., 2000).

CHAPTER 7: MACHINE LEARNING TO PREDICT POST-SECONDARY ENROLMENT

The results from the latent curve modelling analyses (i.e., Chapters 4-6) provided insights into if and when ADHD symptoms, academic outcomes, and symptoms of internalizing disorders differ for the four groups. However, they do not consider the three types of measures together. Furthermore, longitudinal data are not always available or feasible to collect in clinical settings. Thus, the objective for this chapter was to determine how accurately post-secondary enrolment for adolescents with ADHD histories could be predicted using supervised machine learning.

As discussed in Chapter 3, five different machine learning algorithms were employed: Linear Discriminant Analysis (linear), Classification and Regression Trees (nonlinear), *k*-Nearest Neighbors (nonlinear), Support Vector Machine (complex nonlinear) and Random Forests (complex nonlinear). Thirteen variables (a combination of dichotomous, categorical, and continuous) were used as target features: six time-invariant variables (sex, age of biological mom at birth, ethnicity (dummy-coded into Black, Hispanic, and other with White as reference group)), three variables from baseline (advantaged, low-income status, diagnosis of externalizing disorder), and five variables from ages 14 to 17 (WIAT, anxiety symptoms, depression symptoms, inattentive symptoms, hyperactive symptoms). Note that for the five variables from ages 14 to 17, some participants completed the measures more than once. For those participants, scores were averaged. Additionally, the WIAT score was calculated by averaging the three WIAT subtest scores (i.e., mathematics, reading, and spelling). The overall WIAT score was highly correlated with all three subtest scores (rs > .85). Ages 14 to 17 were selected

for academic achievement, ADHD symptoms, and internalizing disorder symptoms because during this time most participants were enrolled in high school and student success in high school determines acceptance into post-secondary programs. Machine learning analyses were conducted in R using the caret package (Kuhn, 2008). Detailed descriptions of the analyses can be found in Appendix A. Code for analyses can be found in Appendix B.

For all analyses, data from 435 of the 520 adolescents with ADHD histories were used. The remaining 85 participants were excluded because they were missing WIAT, ADHD symptoms, and anxiety and depression symptoms scores from ages 14-17. Of the 435 adolescents, 286 (65.7%) eventually enrolled in post-secondary studies. Any missing values (0.09%) were imputed using *k*-Nearest Neighbors because many machine learning algorithms do not support incomplete data sets (Brownlee, 2017). Given that there were more adolescents who eventually enrolled in post-secondary education than not (i.e., the ratio was approximately 2:1), the distribution was not balanced. Imbalanced data can be a problem with machine learning, but typically imbalance is only of concern if the ratio is less than 20% (i.e., 1:4; Krawczyk, 2016). Even when imbalanced data is not a concern, we must consider how it might affect accuracy. With machine learning, we can consider a baseline model which always predicts the most frequent class. In other words, with the present data, a baseline model that only used the frequency of post-secondary enrolment as a feature and classified adolescents as “eventual post-secondary enrolment” 100% of the time would have an accuracy rate of 65.7%. Although the baseline model would accurately classify adolescents two-thirds of the time, note that an adolescent would never be classified as “did not eventually enrol in post-secondary”. Because of this, when

evaluating machine learning results additional measures need to be considered. In the present study, in addition to overall accuracy I report sensitivity, specificity, positive likelihood ratio, negative likelihood ratio, positive predictive value, negative predictive value, prevalence, detection rate, detection prevalence, balanced accuracy, and Kappa value. Each of these measures can be calculated using the values obtained from a confusion matrix (see Table 7.1 for an example). In the confusion matrix, *reference* refers to actual classifications and *predicted* refers to predicted classifications. Each letter (i.e., A, B, C, D) represents the frequency of an event. In addition to the brief descriptions of sensitivity, specificity, positive likelihood ratio, and negative likelihood ratio provided in Chapter 3, Table 7.2 outlines the equations and provides descriptions for the statistics that are reported for each algorithm.

Table 7.1

An Example of a 2x2 Confusion Matrix for a Two-Class Problem

	Reference	
Predicted	Post-Secondary	No Post-Secondary
Post-Secondary	A (True Positives)	B (False Positives)
No Post-Secondary	C (False Negatives)	D (True Negatives)

Table 7.2

Equations and Descriptions of Performance Measures

	Equation	Description
i. Prevalence	$\frac{A+C}{A+B+C+D}$	Total number of adolescents with ADHD histories eventually enrolled in post-secondary studies divided by all adolescents with ADHD histories in the model
ii. Sensitivity	$\frac{A}{A+C}$	Proportion of true positives; Total number of adolescents with ADHD histories who were correctly classified as post-secondary divided by the total number of adolescents with ADHD histories who eventually enrolled in post-secondary studies
iii. Specificity	$\frac{D}{B+D}$	Proportion of true negatives; Total number of adolescents with ADHD histories who were correctly classified as no post-secondary divided by the total number of adolescents with ADHD histories who did not eventually enrol in post-secondary studies
iv. Positive Likelihood Ratio	$\frac{sensitivity}{1-specificity}$	Probability of a true positive divided by the probability of a false positive); Higher ratio desirable
v. Negative Likelihood Ratio	$\frac{1-sensitivity}{specificity}$	Probability of a true negative divided by the probability of a false negative); Higher ratio desirable

vi. Kappa Value	$\frac{observed\ accuracy - expected\ accuracy}{1 - expected\ accuracy}$	Compares observed accuracy (i.e., percentage of correctly classified cases) with expected accuracy (i.e., random chance); Kappa values are always less than or equal to 1; A value < 0 indicates no agreement, 0 to .20 indicates slight agreement, .21 to .40 indicates fair agreement, .41 to .60 indicates moderate agreement, .61 to .80 indicates substantial agreement, and .81 to 1.00 indicates almost perfect agreement between the observed and expected accuracy (Landis & Koch, 1977).
vii. Positive Predictive Value	$\frac{sensitivity * prevalence}{(sensitivity * prevalence) + ((1 - specificity) * (1 - prevalence))}$	Proportion of adolescents with ADHD histories correctly classified as post-secondary; Effected by sample size; Most useful in a medical setting
viii. Negative Predictive Value	$\frac{\text{specificity} * (1 - \text{prevalence})}{((1 - \text{sensitivity}) * \text{prevalence}) + (\text{specificity} * (1 - \text{prevalence}))}$	Proportion of adolescents with ADHD histories correctly classified as no post-secondary; Effected by sample size; Most useful in a medical setting
ix. Detection Rate	$\frac{A}{A + B + C + D}$	Total number of adolescents with ADHD histories who were correctly classified as post-secondary divided by the total sample size

x. Detection Prevalence	$\frac{A + B}{A + B + C + D}$	Total number of adolescents with ADHD histories who were classified as post-secondary (both correctly and incorrectly) divided by the total sample size
xi. Balanced Accuracy	$\frac{sensitivity + specificity}{2}$	Can be used when the classes are imbalanced; Calculated by adding the sensitivity and specificity of the model and dividing that value by 2; Provides a more robust model for improving power in imbalanced data sets (i.e., over-sampling and under-sampling; Velez et al., 2007).

Notes. Higher positive and negative predictive value are indicative of models with a higher probability of correctly classifying people in a given population (Altman & Bland, 1994b). The main difference between sensitivity/specificity and positive/negative predictive value is that sensitivity and specificity are independent of prevalence, whereas positive and negative predictive value take class prevalence into account.

The present analysis consists of a two-class problem: Adolescents are either classified as eventually enrolling in post-secondary studies or not eventually enrolling in post-secondary studies. Sensitivity, specificity, positive predictive value, and negative predictive value are calculated in R using the positive argument. For the present study, "post-secondary" was entered as the positive argument (i.e., the target class). For each confusion matrix, "A" represents cases where the adolescent eventually enrolled in post-secondary studies and the model correctly classified them as post-secondary (i.e., true positives). Similarly, "D" represents cases where the adolescent did not eventually enrol in post-secondary studies and the model correctly classified them as no post-secondary (i.e., true negatives). "B" represents cases where the adolescent did not eventually enrol in post-secondary studies, but the model classified them as post-secondary (i.e., false positives). Finally, "C" represents cases where the adolescent eventually enrolled in post-secondary studies, but the model classified them as no post-secondary (i.e., false negatives).

Training and Testing

The data were inspected to check for any zero or near zero-variance predictors and high correlations (> .80) among predictors. There were no issues with variance or correlations, so all variables were retained for modelling. For all five algorithms, 80% of the data was used for training (n = 348) and 20% was used for testing (n = 87). A function in caret was used to create balanced splits of the data, meaning the random sampling occurs within each class (i.e., post-secondary and no post-secondary), preserving the overall class distribution of the data (Kuhn, 2008). By using this function, both the training and testing data had an approximately 2:1 ratio of post-secondary versus

no post-secondary enrolment classification. Thus, in the training set there were data from 234 adolescents with ADHD histories who eventually enrolled in post-secondary studies and 114 who did not eventually enrol in post-secondary studies. In the testing set there were data from 52 adolescents with ADHD histories who eventually enrolled in post-secondary studies and 35 who did not eventually enrol in post-secondary studies. Information on resampling, cross-validation, and the results of each of the five models are presented in detail in Appendix A. I interpret and synthesize the results at the end of the chapter, comparing the results of the five models.

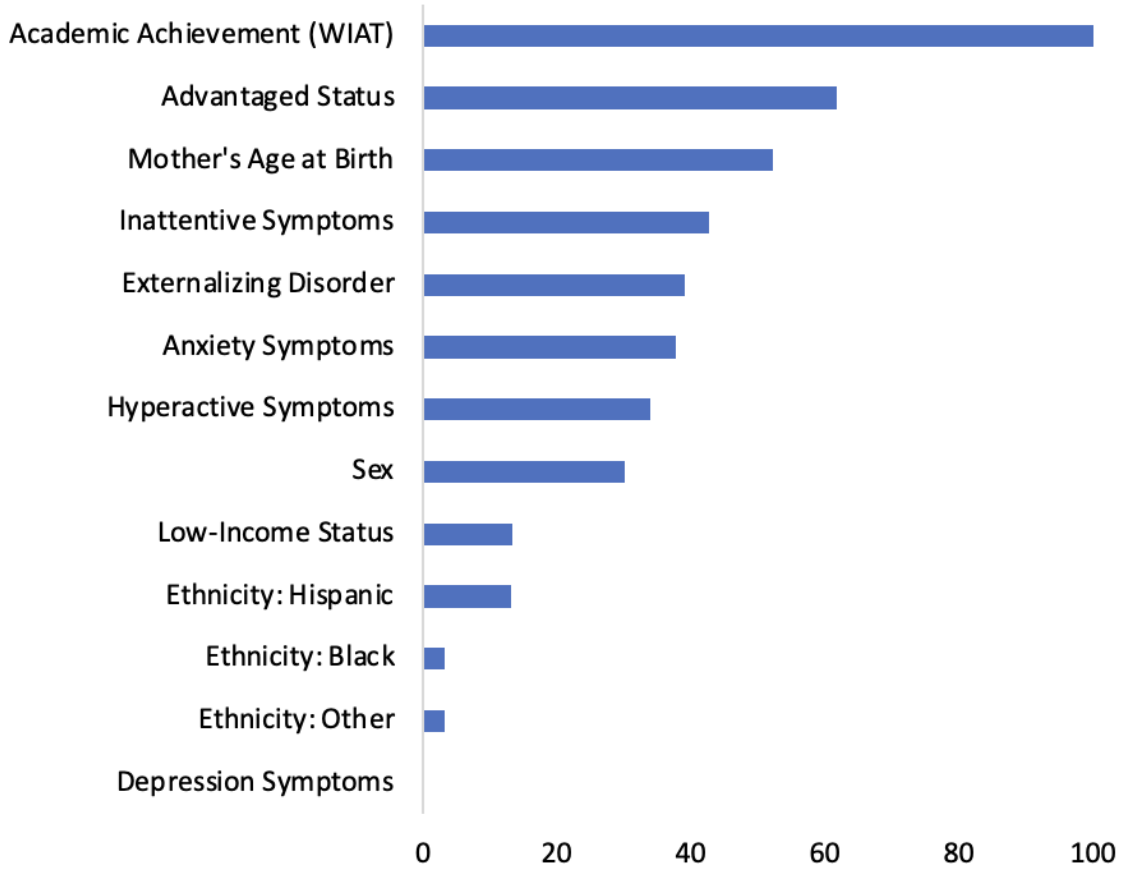
Feature Importance

Features (i.e., variables) entered into the model are not of equal importance. With caret, feature importance can be calculated. Generally speaking, feature importance refers to techniques that assign a score to each input feature based on how useful they are in predicting classification (Brownlee, 2020). Some algorithms, such as CART and RF, use model-specific ways to calculate feature importance (Kuhn, 2008). In contrast, for LDA, *k*-NN, and SVM, caret deploys a default function in which the importance of each feature is evaluated individually using receiver operating characteristic (ROC) curve analysis (see Model Comparison section for more details on ROC). For two-class problems, class is predicted using a series of cut-offs applied to the predictor data. Both sensitivity and specificity are computed for each cut-off and then the ROC curve is computed. The trapezoidal rule, an integration method that can approximate the area under a curve, is used to compute the area under the curve. The resulting area is used as the measure of feature importance. The importance of each feature is then scaled to have a minimum of 0 and a maximum of 100. Figure 7.1 shows the importance of each predictor of post-

secondary enrolment that was included in the model for LDA, *k*-NN, and SVM. The top three features were WIAT, advantaged status, and age of biological mother at birth.

Figure 7.1

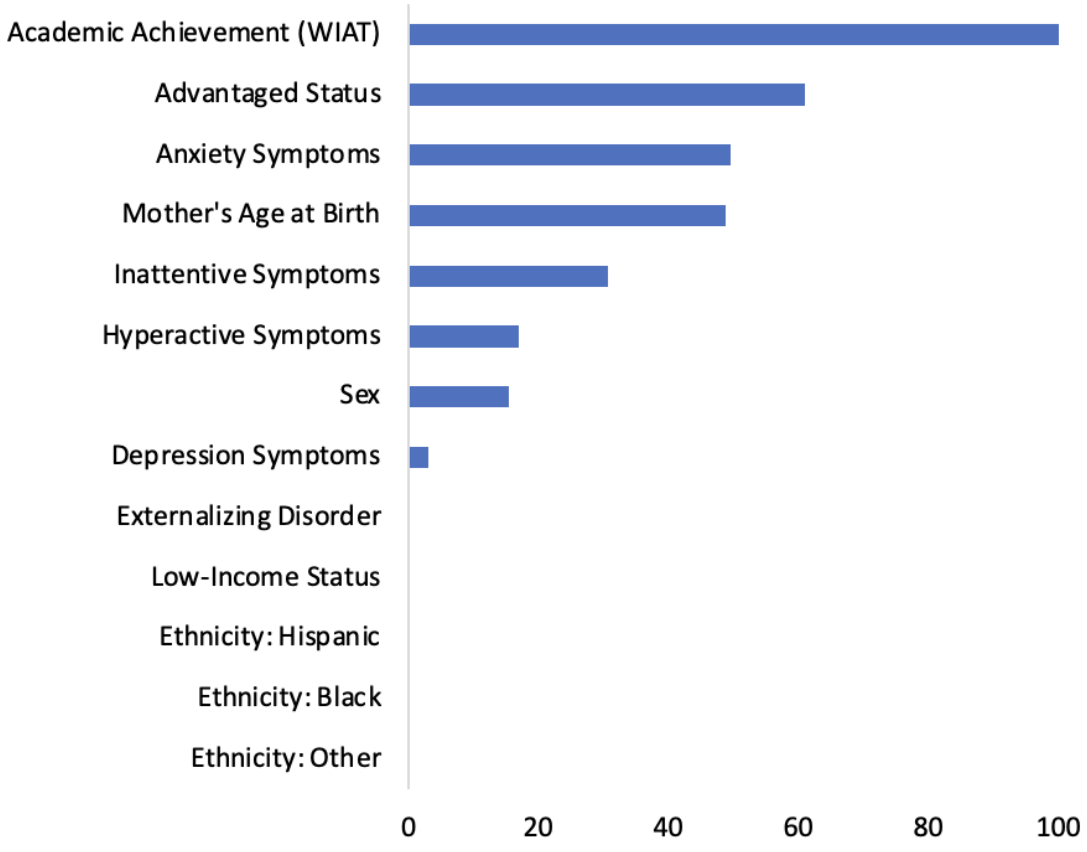
Feature Importance: Linear Discriminant Analysis, k-Nearest Neighbors, and Support Vector Machine



For CART, the reduction in mean squared error attributed to each feature at each split is tabulated and the sum is returned. Sometimes important candidate features are not used in the split. Thus, at each split, the top competing features are also tabulated (Kuhn, 2008). The importance of each predictor is then scaled to have a minimum of 0 and a maximum of 100. Figure 7.2 shows the importance of each predictor of post-secondary enrolment that was included in the CART model. The top three features were WIAT, advantaged status, and anxiety symptoms.

Figure 7.2

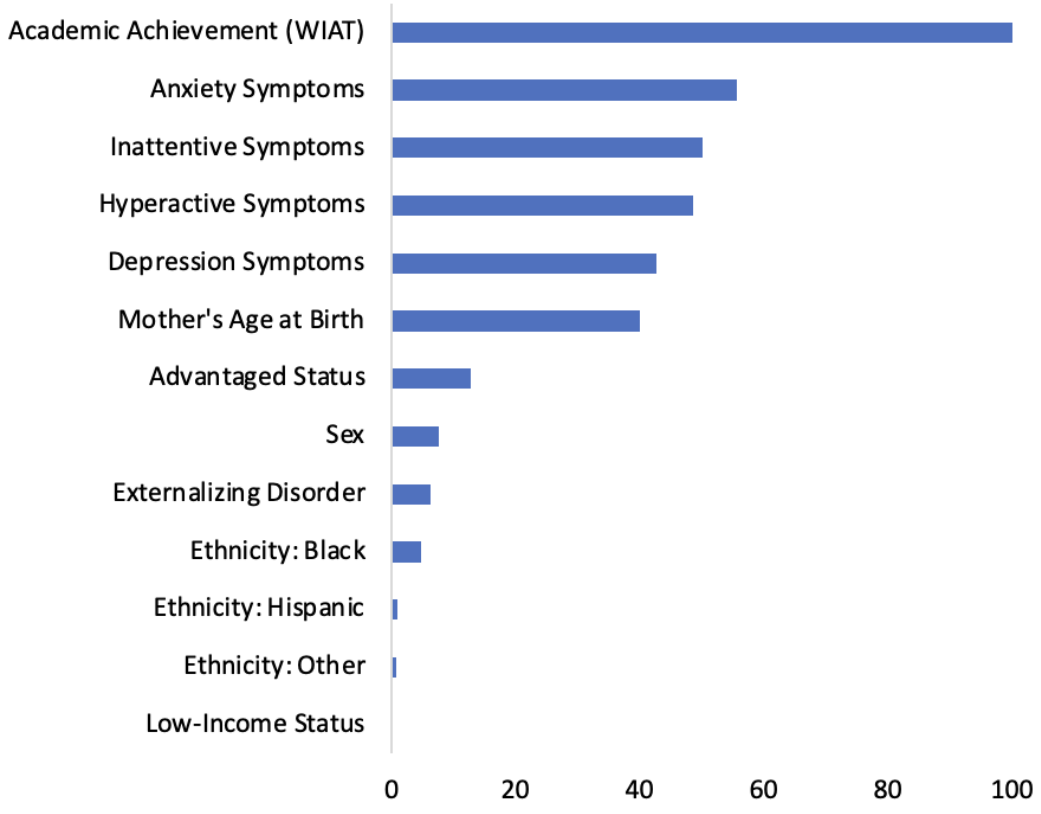
Feature Importance: Classification and Regression Trees



For RF, the prediction accuracy on the out-of-bag portion of data is recorded for each tree. This is repeated after permuting each predictor variable. The difference between the two accuracies is averaged over all trees and normalized by the standard error. If the standard error for a given variable is equal to 0, no division occurs (Kuhn, 2008). The importance of each predictor is then scaled to have a minimum of 0 and a maximum of 100. Figure 7.3 shows the importance of each predictor of post-secondary enrolment that was included in the RF model. The top three features were WIAT, anxiety symptoms, and inattentive symptoms.

Figure 7.3

Feature Importance: Random Forests



Model Comparison

I created and evaluated five different models to see how well each model could predict post-secondary enrolment using data from adolescents with ADHD histories (see Table 7.3 for summary and Appendix A for detailed results). Overall, the models ranged in accuracy from 55% (*k*-NN) to 74% (LDA). All five models were better at predicting adolescents who would eventually attend post-secondary studies compared to those who would not eventually attend post-secondary studies. In general, sensitivity was high across the models, ranging from 79% (*k*-NN) to 92% (LDA). A model with high sensitivity has a higher value of true positives (i.e., adolescents with ADHD histories who were correctly classified as post-secondary) and a lower value of false negatives (i.e., adolescents with ADHD histories who were incorrectly classified as no post-secondary). In contrast, specificity was low across the models, ranging from 20% (*k*-NN) to 54% (RF). A model with low specificity has a lower value of true negatives (i.e., adolescents with ADHD histories who were correctly classified as no post-secondary) and a higher value of false positives (i.e., adolescents with ADHD histories who were incorrectly classified as post-secondary). Together, high sensitivity and specificity are indicative of a model that makes accurate predictions (Altman & Bland, 1994a). Importantly, both sensitivity and specificity should be considered to identify a classifier's strengths as well as its shortcomings.

Table 7.3

Accuracy Statistics for the Five Machine Learning Techniques

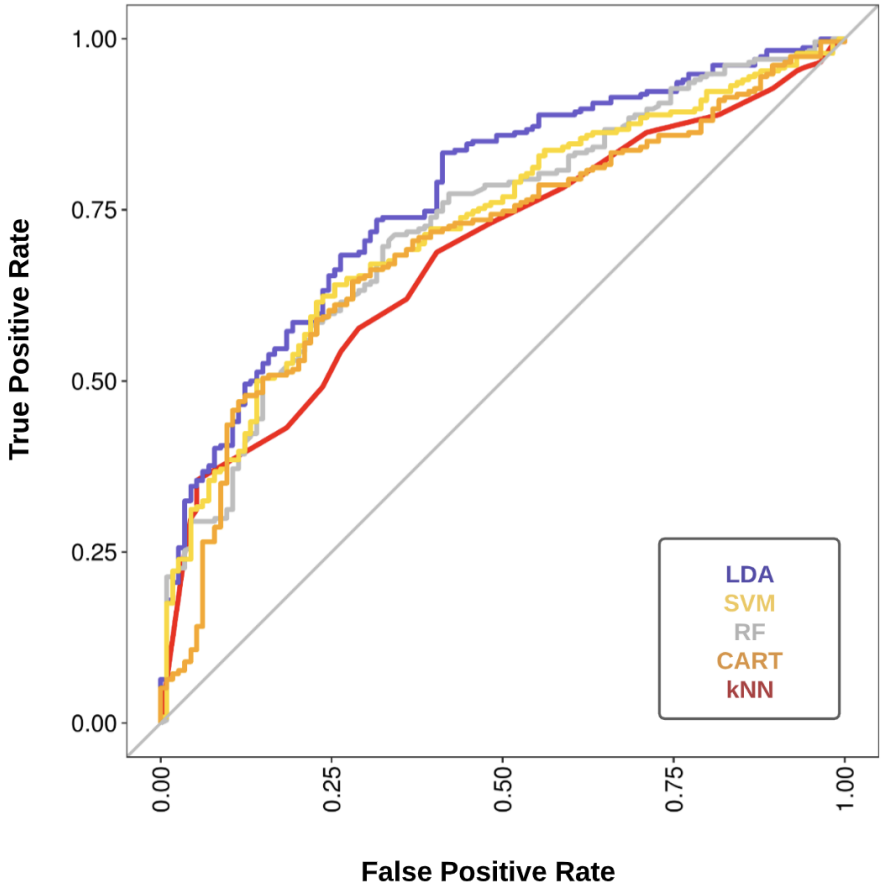
	Proportion				
Model Statistics	LDA	CART	*K*-NN	SVM	RF
Accuracy	0.74	0.70	0.55	0.64	0.72
Prevalence	0.60	0.60	0.60	0.60	0.60
Sensitivity	0.92	0.83	0.79	0.88	0.85
Specificity	0.46	0.51	0.20	0.29	0.54
Positive Likelihood Ratio	1.70	1.70	0.99	1.24	1.85
Negative Likelihood Ratio	0.17	0.34	1.06	0.40	0.28
Kappa Value	0.41	0.35	-0.01	0.19	0.40
Positive Predictive Value	0.72	0.72	0.60	0.65	0.73
Negative Predictive Value	0.80	0.67	0.39	0.63	0.70
Detection Rate	0.55	0.49	0.47	0.53	0.51
Balanced Accuracy	0.69	0.67	0.49	0.59	0.69

Together, specificity and sensitivity can be used to plot receiver operating characteristic (ROC) curves. The ROC is a probability curve created by plotting the true positive rate (i.e., sensitivity) against the false positive rate (i.e., 1-specificity) at various threshold settings. The area under ROC curve (AUC) represents the degree of separability between the classes. An excellent model has an AUC near 1 and a poor model has an AUC near 0. A model with an AUC of .50 is a model that has no class separation capacity. As a rule of thumb, an AUC can be classified as excellent (.9-1.0), good (.8-.9), fair (.7-.8), poor (.6-.7), and failed (.5-.6; Tape, n.d.). The AUC-ROC curve can be used to establish model performance by determining how much the model is capable of distinguishing between the classes (Narkhede, 2018). Figure 7.4 shows the AUC-ROC curves for each of the five machine learning techniques. Overall, the five machine learning techniques had similar performance, with AUC values of .69 (*k*-NN),

.70 (CART), .73 (RF), .73 (SVM), and .77 (LDA). The highest AUC value of .77 suggests that the LDA had fair discriminative ability. That is, it can correctly classify both classes (i.e., post-secondary enrolment and no post-secondary enrolment) 77% of the time. Linear Discriminant Analysis also had the highest accuracy. However, it should be noted that the AUC values were similar across the five algorithms and there was overlap in the curves, suggesting that the LDA is likely not significantly better at distinguishing between the two classes than some of the other algorithms

Figure 7.4

The AUC-ROC Curve for the Five Machine Learning Techniques



Machine Learning Summary

In summary, using five different machine learning techniques resulted in a range of accuracies, but similar AUC values. Five machine learning algorithms were tested to see how accurately adolescents with ADHD histories could be classified as enrolling in post-secondary studies or not. Overall, the five algorithms had a similar pattern of results, and the results mirrored the findings of the latent curve modelling analyses. The most important feature across the algorithms was consistently academic achievement. For the most part, ADHD symptom severity was a moderately important classification feature. With the exception of CART and RF, anxiety and depression symptoms were not strong classification features. Overall, the best models had only fair Kappa values and fair AUC values, correctly classifying adolescents approximately 75% of the time.

There are several possible reasons for the fair results. First, the model was trained and tested on a relatively small data set (with respect to machine learning). If a larger sample of data were available, it is possible the model would have been more accurate as there would have been additional data to train the models and greater predictive power (Beleites et al., 2013).

A second reason that the models were only fair is that the results may reflect the minimal differences between adolescents with ADHD histories who either did or did not eventually enrol in post-secondary studies. As was seen in Chapters 4, 5, and 6, there were few significant differences between adolescents with ADHD histories who did and did not eventually enrol in post-secondary studies. Thus, different features may need to be considered that were not used as part of this thesis, such as parent involvement, peer relationships, academic accommodations, and career goals.

Finally, beyond the present sample it is possible that, regardless of what features are selected, there are not strong, distinguishing features among adolescents with ADHD histories who either do or do not eventually enrol in post-secondary studies. Machine learning may not be a particularly useful technique to try and identify those with ADHD histories who will eventually attend post-secondary because there are likely too many different variables that contribute to a person's decision to enrol in post-secondary studies and these variables may not be consistent across individuals. That is, adolescents with ADHD histories who eventually enrol in post-secondary studies may represent a largely heterogeneous group.

CHAPTER 8: GENERAL DISCUSSION

Is the pattern of development for adolescents with ADHD who eventually attend post-secondary education different from adolescents with ADHD who do not attend post-secondary and their typically developing peers? Attention-deficit/hyperactivity disorder is associated with academic difficulties in childhood and adolescence (Dupaul et al., 2013; Frazier et al., 2007; Kent et al., 2011). Despite these difficulties, many students with ADHD enrol in post-secondary studies. The goal of this thesis was to determine if and when ADHD symptoms, academic outcomes, and symptoms of internalizing disorders differ for adolescents with or without ADHD histories who did or did not eventually enrol in post-secondary studies. In this chapter, I summarize the findings, discuss implications, and address limitations of the present research.

Overview of Thesis

There is an abundance of literature exploring how post-secondary students with ADHD differ from their peers without ADHD as well as literature exploring psychological wellbeing and academic achievement in post-secondary students with ADHD. However, little is known about how people with ADHD who enrol in post-secondary studies differ developmentally from their peers with ADHD who do not enrol. In this thesis, I explored the developmental trajectories of psychological disorders and academic underachievement for adolescents with and without ADHD histories because these factors have longitudinal associations with ADHD (Erskine et al., 2016). My goal was to explore ADHD histories and post-secondary enrolment as factors that may shape the developmental trajectories of ADHD symptoms, academic outcomes (i.e., academic achievement and school performance), anxiety symptoms, and depression symptoms. I

used longitudinal data from the Multimodal Treatment Study of Children with ADHD (MTA) to chart developmental trajectories for four groups: adolescents with ADHD histories and eventual post-secondary enrolment (ADHD Post-Secondary), adolescents with ADHD histories but without post-secondary enrolment (ADHD No Post-Secondary), adolescents without ADHD histories but with post-secondary enrolment (LNCG Post-Secondary), and adolescents with neither ADHD histories nor post-secondary enrolment (LNCG No Post-Secondary).

Using latent curve modelling, I analyzed the trajectories for the four groups. In Table 8.1, I present a snapshot of the findings, marking instances where ADHD status (ADHD), post-secondary status (PS), and the interaction between ADHD status and post-secondary status (ADHD*PS) were significant predictors of the intercept and slope(s) for each of the nine models. For all nine models, the intercept, characterizing one point on the growth curve, was placed at age 13/Grade 8. The intercept effect, therefore, tests whether there were group differences at this point in time. The linear models (i.e., academic achievement) only have one slope (Slope 1), representing the rate of change from ages 9 to 17. The piecewise and cubic models (i.e., ADHD symptoms, school performance, anxiety and depression symptoms) have two slopes representing the rate of change from ages 9 to 13/Grades 6 to 8 (Slope 1) and the rate of change from ages 13 to 17/Grades 9 to 12 (Slope 2). Overall, only trajectories of academic outcomes differed, especially for the two ADHD histories groups. School performance was especially informative, with grades in core subjects (i.e., mathematics and English) declining in middle school for the ADHD No Post-Secondary group and overall GPA improving in high school for the ADHD Post-Secondary group. The developmental trajectories of

ADHD symptoms and symptoms of internalizing disorders did not significantly differ across the four groups. The findings of each model are discussed in more detail in the following sections.

Table 8.1

Summary of Latent Curve Modelling

	Intercept			Slope 1			Slope 2		
	ADHD	PS	ADHD *PS	ADHD	PS	ADHD *PS	ADHD	PS	ADHD *PS
				ADHD Symptoms					
Inattentive Symptoms	✓	✓	X	X	X	X	X	X	X
Hyperactive Symptoms	✓	X	X	X	X	X	✓	X	X
				Affective Symptoms					
Anxiety Symptoms	X	X	X	X	X	X	--	--	--
Depression Symptoms	X	X	X	X	X	X	--	--	--
				Academic Achievement Tests					
WIAT Mathematics	✓	✓	X	X	X	X	--	--	--
WIAT Reading	✓	✓	X	X	X	X	--	--	--
WIAT Spelling	✓	✓	X	✓	X	✓	--	--	--
				School Performance					
Mathematics Grades	X	✓	X	X	X	✓	X	X	X
English Grades	X	✓	X	X	✓	✓	X	X	X
GPA	X	✓	✓	X	X	X	X	X	✓

Note. ✓ significant ($p < .05$), **X** not significant, -- not applicable

ADHD Symptoms

Adolescents with ADHD histories reported more hyperactive and inattentive symptoms than adolescents in the LNCG. Consistent with the existing literature, higher

levels of inattentive symptoms were reported compared to hyperactive symptoms for all four groups (Wasserstein, 2005). Moreover, in adolescence (i.e., ages 13-17) hyperactive symptoms decreased over time for adolescents with ADHD histories. For inattentive symptoms, the progression of ADHD symptoms over time was similar across the four groups. Among adolescents with ADHD histories, statistically, there were no group differences for either mean symptoms of inattention at age 13 or rates of change. However, for four of the machine learning models, ADHD symptoms were moderately important features in predicting post-secondary enrolment for adolescents with ADHD histories. Moreover, although no significant differences were observed, in adolescence (i.e., ages 9-13), inattentive symptoms appeared to level off for the ADHD Post-Secondary group, whereas they appeared to continue increasing for the ADHD No Post-Secondary group. Together these findings provide modest evidence that symptom severity in early adolescence may be associated with later post-secondary enrolment.

In the existing literature, Hechtman et al. (2016) found that adults with symptom-persistent ADHD histories were less likely to obtain a degree than adults with symptom-desistent ADHD histories. Thus, for adolescents with ADHD, we cannot rule out that more severe symptoms of ADHD may have long-term effects on limiting academic opportunities. However, many adolescents with initially severe symptoms do eventually enrol in post-secondary education and thus severe symptoms are not a permanent obstacle for long-term academic opportunities. Overall, clinicians should be mindful of the potential consequences associated with severe symptoms. Symptom management and academic support early in adolescence could promote long-term chances of attending post-secondary education.

Anxiety and Depression Symptoms

Neither ADHD histories nor post-secondary enrolment were associated with mean levels or rates of change in symptoms of anxiety or depression in the present analyses. Similarly, depression symptoms were not an important feature in the machine learning models and anxiety symptoms were only moderately important for two of the models. These findings are consistent with some of the existing literature which has found no moderating effects of depression or anxiety symptoms on academic performance (Becker et al., 2014; Biederman et al., 1996; Heiligenstein et al., 1999; Nelson & Gregg, 2012). These studies found that ADHD symptoms are so strongly associated with academic impairment that the co-occurrence of internalizing symptoms is unlikely to influence this relation. However, the literature has consistently shown that diagnoses of anxiety and depression are more common for people with ADHD histories than those without (Angold et al., 1999; MTA Cooperative Group, 1999b; Schatz & Rostain, 2006; Tannock, 2009). Thus, beyond academic impairment, I expected adolescents with ADHD histories to report more symptoms of anxiety and depression than their typically developing peers. In the present study, which used self-reports, the prevalence of symptoms of internalizing disorders may have been underestimated. In general, boys are likely to underreport such symptoms (Sigmon et al., 2005), self-reports do not always align with clinical judgement (Rynn et al., 2006), and there are limitations of the self-report measures used (Grills-Taquechel et al., 2008). As a result, in the present study, symptoms of internalizing disorders did not provide insights into how the four groups may differ.

Academic Achievement

With respect to academic achievement scores, consistent with other research, adolescents with ADHD histories had lower academic achievement than their typically developing peers (Dupaul et al., 2013; Frazier et al., 2007). Academic achievement scores were also lower for people who did not eventually enrol in post-secondary studies compared to those who did enrol. For all three subsets of academic achievement (i.e., mathematics, reading, and spelling), the ADHD No Post-Secondary group had the lowest scores and the LNCG Post-Secondary had the highest scores. The ADHD Post-Secondary group and LNCG No Post-Secondary group had similar scores, falling between the other two groups.

Scores obtained on academic achievement tests are typically stable over time (Wright, 2010). In the present research, scores were stable for spelling, but decreased slightly for mathematics and reading. With the exception of spelling, neither ADHD histories nor post-secondary enrolment were significant predictors of changes in academic achievement over time. In examining the trajectories, of students who went on to post-secondary education, it is evident that the ADHD group had lower academic achievement than the LNCG at all time points. The gap in academic achievement between the groups was stable from ages 9 to 17.

From a young age (i.e., age 9), children with ADHD histories who eventually enrol in post-secondary studies already had higher academic achievement than their ADHD peers who would not eventually enrol. The gap persisted as children entered adolescence. Moreover, the ADHD Post-Secondary group, on average, had academic achievement scores that were similar to the normative mean of 100. In contrast, the

ADHD No Post-Secondary group, on average, had academic achievement scores below the normative mean. For all machine learning models, academic achievement was the most important feature for classifying students as "post-secondary" versus "no post-secondary" among those with ADHD histories. Taken together, these findings suggest that early identification of children with ADHD who have academic achievement below the normative mean is important. Although academic interventions can be implemented to improve academic achievement for students with ADHD histories, these interventions fall short with respect to narrowing the gap in achievement between those with and without ADHD histories. The results of the present research clearly show that direct interventions may be necessary to ensure that students with ADHD do not fall further behind their typically developing peers and thus have equal long-term academic opportunities (Bikic et al., 2017; Harrison et al., 2019; Moore et al., 2019).

School Performance

Similar to academic achievement, typically developing adolescents who eventually enrolled in post-secondary studies had the highest grades. From Grades 6 to 8 the ADHD Post-Secondary group, ADHD No Post-Secondary group, and LNCG No Post-Secondary had similar mathematics and English grades. However, the grades declined for the ADHD No Post-Secondary group whereas they remained stable (English) or improved (mathematics) for the ADHD Post-Secondary group. Consistent with the existing literature, grades declined for all four groups during the transition from middle to high school (Alspaugh, 1998; Barber & Olsen, 2004). In high school, mathematics and English grades remained stable for all four groups. Thus, parents, educators, and treatment providers need to focus on grades in middle school for children

with ADHD histories and provide additional support to prevent students from falling further behind their peers. Moreover, the decline in grades from Grades 6 through 8 coincides with the time period when the ADHD No Post-Secondary group appeared to have experienced an increase in inattentive symptoms (i.e., ages 11-13). Thus, it is possible that symptom severity in middle school contributed to academic difficulties.

Of most interest was the pattern for overall GPA. The ADHD Post-Secondary group had lower grades in the core subjects of English and mathematics than the LNCG Post-Secondary group. However, in high school the overall GPAs of the ADHD Post-Secondary group improved whereas those of the other groups either remained stable (i.e., LNCG) or declined (i.e., ADHD No Post-Secondary). By the end of high school, the overall GPA for the two post-secondary groups were very similar. Thus, for adolescents with ADHD histories who eventually enrol in post-secondary studies, the improvement in GPA across high school likely contributed to their successful admittance into post-secondary education.

Using data from the Pittsburgh ADHD Longitudinal Study, Kent et al. (2011) also found that GPA slightly improved in high school for students with ADHD histories, but slightly declined for their typically developing peers. The improvement throughout high school remained even when GPA was divided into academic GPA (i.e., English, mathematics, social studies, and science) and overall GPA (i.e., both academic and elective courses). Kent et al. propose that adolescents with ADHD may take easier academic loads after completing required courses, they may have a gradual adaptation to the high school environment, or they may re-take failed courses and improve the second time. However, in Kent et al., students were not divided based on post-secondary

enrolment and thus adolescents with ADHD histories had lower GPA in all years of high school than their typically developing peers. In contrast, in the present study, the ADHD Post-Secondary group had similar GPAs to the LNCG Post-Secondary by the time they reached Grade 12, highlighting the importance of considering eventual post-secondary enrolment as a factor of school performance. Overall, high school appears to be a critical period for adolescents with ADHD who eventually enrol in post-secondary studies, however, why these students started to improve remains unclear.

The different patterns between the two ADHD histories groups highlights the diversity of outcomes among children with ADHD histories (Cicchetti & Rogosch, 1996; Merrill et al., 2020). Although the children in these two groups had similar histories, their developmental outcomes differed, with diverging trajectories emerging in middle school for core school subjects (i.e., mathematics and English) and in high school for overall GPA. However, despite the gains of the ADHD Post-Secondary group, on average they still had lower academic achievement and English and mathematics grades than the LNCG Post-Secondary. Thus, they entered post-secondary education less strong academically than their typically developing peers. This disadvantage may have implications for their success in post-secondary. Consistent with this finding, university students with ADHD typically struggle academically in university, are less confident in their ability to academically succeed, and have lower graduation rates (Blase et al., 2009; Green & Rabiner, 2012; Heiligenstein et al., 1999; Kane et al., 2011; Lewandowski et al., 2008; Shaw-Zirt et al., 2005).

Overall, adolescents with ADHD histories had poorer academic outcomes than their typically developing peers. When separating adolescents with ADHD histories

based on eventual post-secondary enrolment, academic outcomes were superior for the adolescents who eventually enrolled in post-secondary studies than those who did not, however, they still had poorer outcomes than their typically developing peers who eventually enrolled. To help students with ADHD succeed academically, educators could change the classroom environment and school context to make it more accommodating for students with ADHD. For example, although many students with ADHD receive academic accommodations, such as extra time for tests, writing tests in a separate room, or having tests read aloud by a teacher (Lovett & Lewandowski, 2015), these accommodations rarely improve students' performance and do not have benefits that are specific to students with ADHD (Lovett & Nelson, 2020). Instead, instructional design changes that support a more inclusive classroom and reduce the need for special accommodations may have academic benefits for all (Loe & Feldman, 2007; McGuire et al., 2003). Moreover, outside of the classroom, school-based interventions, such as organizational skills training, instructional interventions (i.e., flash cards, writing strategy training), social skills training, and daily report cards have been found to be effective with students with ADHD (Bikic et al., 2017; Harrison et al., 2019; Moore et al., 2019).

Comparing Academic Outcomes

How academic outcomes are measured provide further insights into if and when adolescents from the four groups may differ. Previous research has suggested that standardized achievement and school performance should be considered separately (Raggi & Chronis, 2006). In the present research, both types of academic achievement differentiated the four groups, but the trajectories were different for academic achievement and school performance. More specifically, academic achievement slightly

declined for all four groups over time, but with the exception of spelling, the rates of change did not differ for the four groups. Thus, if we only consider standardized academic achievement, there does not appear to be a critical time period in which the ADHD Post-Secondary group began to differ from the ADHD No Post-Secondary group. In contrast, for school performance in core subjects (i.e., mathematics and English) there was a significant decline in grades for the ADHD No Post-Secondary group during middle school. Moreover, for overall GPA, there was a significant improvement for the ADHD Post-Secondary group. Thus, considering school performance is important for identifying critical periods of change for those with ADHD histories.

One possibility for the difference in trajectories between academic achievement and school performance is that academic achievement may be less affected by the numerous factors that influence school success. For example, for students to be successful in school they must not only learn and retain new information, but they must work well with peers and teachers, be motivated to succeed, regularly attend classes, take notes, and complete homework and assignments (Arnold et al., 2020; Raggi & Chronis, 2006). Moreover, academic achievement tests focus on core subjects, such as reading, writing, and mathematics. In contrast, school performance is based on a variety of subjects, such as art, history, geography, gym, and science. Thus, the differences in academic achievement and school performance trajectories may reflect the different skills needed for school success versus success on standardized academic achievement tests.

A second possibility is that the improvement in GPA reflects motivation and engagement in school. In high school, students have more freedom to select courses that are of interest to them, thus, the improvement in overall GPA may reflect motivation for

subjects that are of interest to the ADHD Post-Secondary group. Along with more freedom to select courses comes increased expectations for self-regulated learning, which is supported by intrinsic motivation, extrinsic motivation, and goal-directed executive functions (Kim, 2013; Zimmerman, 2002). With regard to academics, students with ADHD reported less intrinsic motivation (Carlson et al., 2002; Morsink et al., 2017) and less extrinsic motivation (Barron et al., 2006; Colomer et al., 2017; Gut et al., 2012; Olivier & Steenkamp, 2004; Zentall & Beike, 2012). Motivation may be lower among students with ADHD because they have learning-related problems which makes schoolwork more aversive to them (Loe & Feldman, 2007). The schoolwork is also tailored to the needs and skills of their typically developing peers. Academic accommodations are supposed to give students with disabilities an equal opportunity to benefit from the educational process. However, these accommodations likely are not adequate, and thus we continue to see large discrepancies in school performance between those with and without ADHD histories. Moreover, students with ADHD have a preference for immediate reward and show reduced sensitivity to future negative consequences (Scheres et al., 2006; Toplak et al., 2005). Combined, high school students with ADHD histories may not be adequately accommodated and may be less motivated to achieve high grades because of previous negative school experiences, need for instant reward, and indifference for future negative consequences of academic failure.

Developmentally, school failures and negative feedback from parents and teachers in elementary and middle school can lead to reduced self-efficacy and competence-related beliefs for high school students (Newark et al., 2016). Regardless of ADHD histories, competence beliefs for different tasks decline in late childhood and early

adolescence (Wigfield, Eccles, et al., 2006). However, there is considerable variation in the pattern of decline. As students get older, they become more accurate in their self-assessments through improved understanding, interpretation, and integration of feedback from adults, and through comparisons with their peers (Eccles et al., 1998; Nicholls, 1984; Wigfield, Byrnes, et al., 2006). Moreover, the school environment is heavily focused on evaluation; as students get older, they begin to compete with their peers. For those students who frequently receive negative evaluations of their competence, self-assessments of competence may continue to decline and their negative self-beliefs can cause students to give up hope that they can be successful in school (Dweck, 2006). For students with ADHD who have likely faced years of academic struggles, by the time they reach high school they may not make as much effort in school as their peers because they believe there is a low probability of achieving high grades. In the present study, this may have been the case for the ADHD No Post-Secondary group who consistently achieved lower grades than their peers.

A third possibility is that poor school performance may result from deficits in goal-directed executive functions (Gollwitzer & Brandstatter, 1997; Zimmerman, 2002). Executive function pertains to cognitive processes, such as working memory, response inhibition, and cognitive flexibility, that facilitates problem solving and supports the completion of goals in the future (Kim, 2013; Pennington & Ozonoff, 1996). Executive functions support goal-directed behaviours for academic tasks, like engagement, planning, initiation, and inhibition of unproductive behaviours (Kim, 2013). In high school, executive functions are particularly important because the environment is less structured than in elementary and middle school. Students are offered fewer prompts, less

assistance, and limited immediate reinforcement from their teachers. In adolescence, the prefrontal cortex, which is essential to executive function, develops substantially, leading to improved cognitive control (Blakemore & Choudhury, 2006; Sowell et al., 2007). Deficits in executive function and goal-directed behaviours are linked to poorer academic performance in persons with ADHD (Gropper & Tannock, 2009; Langberg et al., 2013; Sibley et al., 2019). Moreover, students' weaknesses in executive function may be more closely related to symptoms of inattention than to those of hyperactivity-impulsivity (Sonuga-Barke, 2005). These weaknesses in executive function appear to be persistent, rather than reflecting a delay in maturation of executive function for adolescents with ADHD (Martel et al., 2007).

In the present study, the ADHD No Post-Secondary group appeared to have more severe inattentive ADHD symptoms in adolescence than the ADHD Post-Secondary group. Given the link between executive function weaknesses and inattentive symptoms, and the importance of executive function and goal-directed behaviours for academic success, it is possible that the ADHD Post-Secondary group had less impaired executive function than the ADHD No Post-Secondary group, which in turn made them less susceptible to academic failure. If executive function weaknesses are already present in childhood (Willcutt et al., 2005) and persist into adolescence (Sibley et al., 2019), then the ADHD No Post-Secondary group, who had more severe inattentive symptoms, may have had executive function weaknesses and problems with self-regulated learning throughout school. High school may have been particularly challenging, as more goal-directed behaviours are required for the less-structured high school environment. Thus, it may be important to implement interventions to improve self-regulated learning before

adolescents with ADHD histories begin high school. For example, interventions could focus on improving goal setting, planning, organization, and reducing off-task behaviours and procrastination (Gawrilow et al., 2013; Sibley et al., 2016; Sprich et al., 2016).

A final consideration is the relation between treatment and academic improvement. In a 2020 review, Arnold concludes that long-term academic outcomes, as measured by both standardized academic achievement and academic performance in school, are adversely affected by ADHD. People with untreated ADHD had considerably more negative academic outcomes than those with treated ADHD. However, for those who received treatment, improvements in academic achievement were greater than improvements in school performance. In studies that controlled for IQ, students who received treatment showed academic improvement in all studies using academic achievement outcomes (i.e., 100% of studies) whereas improvements were only found in 57% of studies with school performance outcomes (Arnold et al., 2020). Improved academic outcomes were most consistently associated with multimodal treatment, but nonetheless there was still significantly more improvement in standardized academic achievement (100%) than school performance (67%). Thus, treatment for ADHD consistently led to improvement in academic achievement but did not always lead to improvement in school performance.

These different patterns of treatment effects on academic achievement versus school performance highlight the importance of considering the different types of academic outcomes separately in research and may also support the need for persistent treatment of ADHD. Although 80% of children and adolescents with ADHD benefit from medication treatment (Antshel, 2015), some adolescents with ADHD only experience

partial benefits and long-term effectiveness of medication treatment has not been established (Daley et al., 2014). In the MTA sample, 62% of adolescents who were taking medication during the 14 months of treatment stopped medication by the 8-year follow-up (Molina et al., 2009). Thus, consistent and persistent medication treatment and behavioural interventions, like ADHD coaching which targets the necessary skills required for academic success, such as goal-setting, organization, time management, and self-monitoring, may be particularly beneficial for adolescents with ADHD when they transition into high school (Ahmann et al., 2017).

Overall, when comparing the developmental trajectories of adolescents with or without ADHD histories who did or did not eventually enrol in post-secondary studies, differences were evident in academic outcomes. Importantly, there were school performance differences in middle school and high school between the two ADHD groups. Moreover, all five machine learning models indicated that academic achievement was the most important feature when classifying adolescents with ADHD histories as either “post-secondary” or “no post-secondary”. There was some evidence for differences in inattentive symptom severity during adolescence, but no evidence for differences in symptoms of internalizing disorders. Thus, when considering ADHD symptoms, academic outcomes, and symptoms of internalizing disorders, only academic outcomes significantly explained differences across the four groups. However, many factors may contribute to academic outcomes which, in turn, indirectly contribute to post-secondary enrolment. In future research, external factors could be considered, such as familial support and involvement, interest in school, career goals, and availability of accommodations.

Limitations and Future Research

One limitation is that all adolescents with ADHD histories, regardless of comorbidity, were grouped together in the analyses. As was discussed previously, people with both ADHD and a second psychological disorder may have a different presentation and respond differently to treatment than ADHD alone. This effect of co-morbidity may be especially important for those with comorbid externalizing disorders, such as Oppositional Defiance Disorder or Conduct Disorder (MTA Cooperative Group, 1999a, 1999b). Students with comorbid disorders have lower academic performance and more problems with homework than their peers with ADHD only (Karustis et al., 2000; Mounteaux et al., 2007). Moreover, ADHD is highly comorbid with learning disorders; approximately 20% of MTA children had a reading learning disorder (Hechtman et al., 2005). Although I controlled for the presence of externalizing disorders in the present study, in future studies it would be interesting to examine separate trajectories for ADHD only, ADHD + internalizing disorders, and ADHD + externalizing disorders to see if there are any developmental differences among the three groups, as it has been suggested that these may represent three distinct ADHD classifications (Jensen et al., 2001). Similarly, it would be interesting to examine separate trajectories for ADHD + learning disorders because learning disorders likely have an additive negative impact on school performance (Mayes et al., 2000).

A second limitation is that participants were classified as enrolling in post-secondary education if they attended either community college or university. Admittance to university is often more competitive and requires higher grades in high school than admittance to community college. Moreover, the courses taken in high school often differ

for students who plan to pursue university versus students who plan to pursue community college. Although I could not decisively determine who went to community college versus university, based on the demographic information obtained, I estimated that 80% of the LNCG Post-Secondary enrolled in university programs (i.e., degree programs) compared to only 55% of the ADHD Post-Secondary group. This is consistent with other research which has found that fewer adolescents with ADHD complete degree programs in comparison to their typically developing peers (Barkley et al., 2008). Given this difference in the type of post-secondary enrolments, it is also possible that the improved GPA in high school reflected a shift to college-level preparatory courses. There are many students who do not wish to pursue university education. Similarly, there are many students who do not wish to pursue community college education. However, it is important that students who want to attend university because their ultimate career goals require a university degree be given the opportunity. From that perspective, further distinguishing adolescents with ADHD histories who attended community college versus university may provide insights into different patterns of academic achievement and school performance and allow for targeted intervention so that students achieve their educational potential.

Finally, although not a direct limitation of the present study, I acknowledge that only so many factors could be considered in one study. I chose to examine ADHD symptoms, academic outcomes, and internalizing disorders because previous literature has found longitudinal associations between ADHD histories and adverse outcomes, such as mental disorders and academic underachievement (Erskine et al., 2016). However, several additional factors may influence whether or not a person enrols in and completes

post-secondary studies. For example, using the MTA data, Howard et al. (2016) found that for those with and without ADHD histories, parent involvement during adolescence, combined with post-secondary attendance after high school, was associated with lower rates of impairment in adulthood. In another study using MTA data, Mrug et al. (2012) found that peer rejection predicted negative outcomes, including delinquency, anxiety, and global impairment. Thus, in future studies, researchers might examine whether parenting and peer relationships partially mediate the relation between academic outcomes and eventual post-secondary enrolment.

Additionally, executive functioning has been linked to impairments and academic outcomes (Boonstra et al., 2005; Loe & Feldman, 2007), so it is possible that executive functioning may be a strong differentiator of whether adolescents enrol in post-secondary education. Finally, it may be worth investigating the types of accommodations that students received while in school, such as notetakers, extra time, and extended deadlines. In general, there are several variables that may influence eventual post-secondary attendance that should be considered in future research.

Conclusion

In conclusion, the present study sought to provide insights into factors that may differentiate adolescents with or without ADHD histories who did or did not eventually enrol in post-secondary studies. Overall, adolescents with ADHD histories who enrolled in post-secondary studies were “high achieving” in the sense that they had better academic outcomes than their ADHD peers who did not enrol. In particular, their performance on academic achievement tests looked similar to their peers without ADHD who did not enrol in post-secondary studies. With the exception of overall GPA in high

school, on average, the ADHD Post-Secondary group had poorer academic outcomes than the LNCG Post-Secondary. Thus, despite achieving high enough grades to be accepted to postsecondary education, these adolescents are presumably still less prepared academically than their peers who were never diagnosed with ADHD. Nonetheless, in general, they had better academic outcomes than their peers with ADHD who did not enrol in post-secondary studies.

Overall, longitudinal associations exist between ADHD and mental disorders and academic underachievement. However, in the present research, neither ADHD symptom severity nor symptoms of internalizing disorders statistically differed for the two ADHD groups. These two groups were differentiated, however, by their academic outcomes. Developmentally, differences in school performance appeared in middle school and high school. For adolescents with ADHD histories, those who did not eventually enrol in post-secondary studies had poorer grades in core subjects in middle school and consistently poor GPA in high school, whereas those who did eventually enrol in post-secondary studies had improvements in GPA in high school, eventually performing similarly to their typically developing peers who enrolled. Thus, to ensure students have an equal opportunity for long-term academic outcomes, it may be particularly important for parents, educators, and clinicians to pay attention to students who have low academic achievement scores, students who have declining grades in middle school, and students with more severe ADHD symptoms. Interventions targeted toward improving academic outcomes such as classroom modifications and accommodations for children with ADHD, persistent treatment, and coaching strategies may be important ways to support the academic achievements of adolescents with ADHD.

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APPENDICES

Appendix A: Machine Learning Results

Resampling

A model parameter is a variable whose value is estimated from a given data set. For example, with regression, the regression line is the model that is used to predict values of y for given values of x. In machine learning, model parameters are estimated from the training data, thus, the model parameters or variables are internal to the machine learning model (Paturu, 2019). A model hyperparameter is set prior to model training; it controls an aspect of the model training process. For example, in *k*-NN, a hyperparameter would be used to control or select the value for *k*. Different algorithms use different hyperparameters and these hyperparameters can be difficult to specify. With caret, the trainControl function can be used to generate the optimal hyperparameters for a given algorithm. For LDA and CART, 10-fold cross-validation was used. Cross-validation can be particularly useful when trying to evaluate models on a limited data sample (Brownlee, 2018). With 10-fold cross-validation, the data set is shuffled randomly and then split into ten groups. For each unique group, that group is taken as a test data set and the remaining groups are taken as a training data set. The model is fit on the training data set and evaluated on the test data set. The evaluation score is retained, and the model is discarded. The skill of the model is summarized using the sample of model evaluation scores. Each observation in the data set is assigned to one of the ten groups and remains in that group for the duration of the procedure. This gives each sample the opportunity to be used once in the testing data set and nine times in the training data set (James et al., 2013).

For *k*-NN and RF, repeated cross-validation was used. This is similar to cross-validation, but the 10-fold cross-validation is repeated *n* number of times. In the present analyses, cross-validation was repeated three times. The final model accuracy is the mean from the three repeats. Repeated cross-validation gives a more robust model assessment score than cross-validation. Repeated cross-validation is beneficial for *k*-NN because it can help with selecting the appropriate "*k*" value. In the present analyses, repeated cross-validation decided on an optimal *k* value of 9. Repeated cross-validation is also beneficial for RF because it can help with selecting the appropriate mtry parameter. The mtry parameter refers to the number of variables available for splitting at each tree node. This parameter is thought to have a strong influence on estimates of predictor variable importance (Strobl & Zeileis, 2008). In the present analyses, repeated cross-validation decided on an optimal mtry value of 5.

For SVM, repeated cross-validation was used, specifying three repetitions. Additionally, a tuning parameter was included to avoid overfitting the model. A standard SVM does not allow any points to be misclassified, which can result in either an overfit model or a model where no decision boundary can be found (Yildirim, 2020). An overfit model can accurately classify the training data but is often inaccurate on the test data because the model is sensitive to noise, and small changes in data points could change the classification results. To avoid this, a soft margin SVM can be conducted which allows some data points to be misclassified or be on the wrong side of the decision boundary. The goals of a soft margin SVM are to increase the distance of the decision boundary to classes and maximize the number of points that are correctly classified in training. The trade-off between these two goals is controlled by the C parameter, which adds a penalty

for each misclassified data point. C values typically range between 0.1 and 100. A small C value suggests the penalty is low, so the chosen decision boundary will be one with a large margin at the expense of more misclassifications. A large C value suggests the penalty for misclassification is high, so the chosen decision boundary will be one with a small margin. The penalty is directly proportional to the distance to the decision boundary. As was discussed in Chapter 3, real data is rarely linearly separable. Thus, given that the present analyses use a Radial Basis Function Kernel, in addition to C, gamma must also be considered. Gamma values typically range between 0.0001 and 10. Gamma controls for the distance of influence of a single training point (Yildirim, 2020). Low values of gamma are indicative of a large similarity radius, resulting in more points being grouped together. In contrast, with high values of gamma, data points are grouped in the same class if they fall in a tightly bounded area. In general, large gamma values result in overfit models. For good accuracy, it is essential that appropriate values of C and gamma are selected and that both values are optimized simultaneously. With caret, the tuneLength parameter instructs the algorithm to try different values for the main parameter, C, while holding gamma constant. In the present analyses, the tuneLength was set to 10, meaning the algorithm tried 10 different values of C. Gamma was held constant at 0.0629 and the optimal model for C was found to be 1.00.

Linear Discriminant Analysis (LDA)

Table A1 is the confusion matrix. Table A2 outlines the results when the information from Table A1 is used to compute Equations (i) through (xi) from Chapter 7. Overall, the model accurately classified adolescents with ADHD histories as having enrolled in post-secondary studies 73.56% of the time. The Kappa value of .4089

indicates fair to moderate agreement between the observed and expected accuracy (Landis & Koch, 1977). The model had much higher sensitivity (92.31%) than specificity (45.71%). Taking prevalence into account, the model had higher positive predictive value (71.64%) than negative predictive value (45.71%). Overall, the model was more accurate at predicting adolescents with ADHD histories who eventually enrolled in post-secondary studies than adolescents with ADHD histories who did not eventually enrol in post-secondary studies. With a Bayes' nomogram, the prevalence rate and positive likelihood ratio were used to determine that there was approximately a 75% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as Post-Secondary. Similarly, with a Bayes' nomogram, the prevalence rate and negative likelihood ratio were used to determine that there was approximately a 25% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as No Post-Secondary.

Table A1

Confusion Matrix: Linear Discriminant Analysis

	Reference	
Predicted	Post-Secondary	No Post-Secondary
Post-Secondary	48 (True Positives)	19 (False Positives)
No Post-Secondary	4 (False Negatives)	16 (True Negatives)

Table A2

Accuracy Statistics: Linear Discriminant Analysis

Model Statistics	Proportion
Accuracy	.7356
Prevalence	.5977
Sensitivity	.9231
Specificity	.4571
Positive Likelihood Ratio	1.7003
Negative Likelihood Ratio	0.1682
Kappa Value	.4089
Positive Predictive Value	.7164
Negative Predictive Value	.8000
Detection Rate	.5517
Balanced Accuracy	.6901

Classification and Regression Trees (CART)

Table A3 is the confusion matrix. Table A4 outlines the results when the information from Table A3 is used to compute Equations (i) through (xi) from Chapter 7. Overall, the model accurately classified adolescents with ADHD histories as having enrolled in post-secondary studies 70.11% of the time. The Kappa value of .3545 indicates fair agreement between the observed and expected accuracy (Landis & Koch, 1977). The model had higher sensitivity (82.69%) than specificity (51.43%). Taking prevalence into account, the model had a slightly higher positive predictive value (71.67%) than negative predictive value (66.67%). Overall, the model was more accurate at predicting adolescents with ADHD histories who eventually enrolled in post-secondary studies than adolescents with ADHD histories who did not eventually enrol in post-secondary studies. With a Bayes' nomogram, the prevalence rate and positive likelihood ratio were used to determine that there was approximately a 75% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the

model classified them as Post-Secondary. Similarly, with a Bayes' nomogram, the prevalence rate and negative likelihood ratio were used to determine that there was approximately a 38% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as No Post-Secondary.

Table A3

Confusion Matrix: Classification and Regression Trees

	Reference	
Predicted	Post-Secondary	No Post-Secondary
Post-Secondary	43 (True Positives)	17 (False Positives)
No Post-Secondary	9 (False Negatives)	18 (True Negatives)

Table A4

Accuracy Statistics: Classification and Regression Trees

Model Statistics	Proportion
Accuracy	.7011
Prevalence	.5977
Sensitivity	.8269
Specificity	.5143
Positive Likelihood Ratio	1.7025
Negative Likelihood Ratio	0.3366
Kappa Value	.3545
Positive Predictive Value	.7167
Negative Predictive Value	.6667
Detection Rate	.4943
Balanced Accuracy	.6706

K-Nearest Neighbors

Table A5 is the confusion matrix. Table A6 outlines the results when the information from Table A5 is used to compute Equations (i) through (xi) from Chapter 7. Overall, the model accurately classified adolescents with ADHD histories as having enrolled in post-secondary studies only 55.17% of the time. The Kappa value of -.0125 indicates no agreement between the observed and expected accuracy (Landis & Koch, 1977). The model had much higher sensitivity (78.85%) than specificity (20.00%). Taking prevalence into account, the model had a slightly higher positive predictive value (59.42%) than negative predictive value (38.89%). Overall, the model was more accurate at predicting adolescents with ADHD histories who eventually enrolled in post-secondary studies than adolescents with ADHD histories who did not eventually enrol in post-secondary studies. With a Bayes' nomogram, the prevalence rate and positive likelihood ratio were used to determine that there was approximately a 65% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as Post-Secondary. Similarly, with a Bayes' nomogram, the prevalence rate and negative likelihood ratio were used to determine that there was approximately a 65% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as No Post-Secondary.

Table A5

Confusion Matrix: K-Nearest Neighbors

	Reference	
Predicted	Post-Secondary	No Post-Secondary
Post-Secondary	41 (True Positives)	28 (False Positives)
No Post-Secondary	11 (False Negatives)	7 (True Negatives)

Table A6

Accuracy Statistics: K-Nearest Neighbors

Model Statistics	Proportion
Accuracy	.5517
Prevalence	.5977
Sensitivity	.7885
Specificity	.2000
Positive Likelihood Ratio	0.9856
Negative Likelihood Ratio	1.0575
Kappa Value	-.0125
Positive Predictive Value	.5962
Negative Predictive Value	.3889
Detection Rate	.4713
Balanced Accuracy	.4942

Support Vector Machine

Table A7 is the confusion matrix. Table A8 outlines the results when the information from Table A7 is used to compute Equations (i) through (xi) from Chapter 7. Overall, the model accurately classified adolescents with ADHD histories as having enrolled in post-secondary studies 64.37% of the time. The Kappa value of .1869 indicates slight agreement between the observed and expected accuracy (Landis & Koch, 1977). The model had much higher sensitivity (88.46%) than specificity (28.57%). Taking prevalence into account, the model had similar positive predictive value (64.79%) and negative predictive value (62.50%). Overall, the model was more accurate at predicting adolescents with ADHD histories who eventually enrolled in post-secondary

studies than adolescents with ADHD histories who did not eventually enrol in post-secondary studies. With a Bayes' nomogram, the prevalence rate and positive likelihood ratio were used to determine that there was approximately a 68% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as Post-Secondary. Similarly, with a Bayes' nomogram, the prevalence rate and negative likelihood ratio were used to determine that there was approximately a 40% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as No Post-Secondary.

Table A7

Confusion Matrix: Support Vector Machine

	Reference	
Predicted	Post-Secondary	No Post-Secondary
Post-Secondary	46 (True Positives)	25 (False Positives)
No Post-Secondary	6 (False Negatives)	10 (True Negatives)

Table A8

Accuracy Statistics: Support Vector Machine

Model Statistics	Proportion
Accuracy	.6437
Prevalence	.5977
Sensitivity	.8846
Specificity	.2857
Positive Likelihood Ratio	1.2384
Negative Likelihood Ratio	0.4039
Kappa Value	.1869
Positive Predictive Value	.6479
Negative Predictive Value	.6250
Detection Rate	.5287
Balanced Accuracy	.5852

Random Forests

Table A9 is the confusion matrix. Table A10 outlines the results when the information from Table A9 is used to compute Equations (i) through (xi) from Chapter 7. Overall, the model accurately classified adolescents with ADHD histories as having enrolled in post-secondary studies 72.41% of the time. The Kappa value of .4041 indicates fair to moderate agreement between the observed and expected accuracy (Landis & Koch, 1977). The model had higher sensitivity (84.62%) than specificity (54.29%). Taking prevalence into account, the model had a slightly higher positive predictive value (73.33%) than negative predictive value (70.37%). Overall, the model was more accurate at predicting adolescents with ADHD histories who eventually enrolled in post-secondary studies than adolescents with ADHD histories who did not eventually enrol in post-secondary studies. With a Bayes' nomogram, the prevalence rate and positive likelihood ratio were used to determine that there was approximately a 75% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as Post-Secondary. Similarly, with a Bayes' nomogram, the prevalence rate and negative likelihood ratio were used to determine that there was approximately a 33% chance that a person with a history of ADHD would eventually enrol in post-secondary studies given that the model classified them as No Post-Secondary.

Table A9

Confusion Matrix: Random Forests

	Reference	
Predicted	Post-Secondary	No Post-Secondary
Post-Secondary	44 (True Positives)	16 (False Positives)
No Post-Secondary	8 (False Negatives)	19 (True Negatives)

Table A10

Accuracy Statistics: Random Forests

Model Statistics	Proportion
Accuracy	.7241
Prevalence	.5977
Sensitivity	.8462
Specificity	.5429
Positive Likelihood Ratio	1.8512
Negative Likelihood Ratio	0.2833
Kappa Value	.4041
Positive Predictive Value	.7333
Negative Predictive Value	.7037
Detection Rate	.5057
Balanced Accuracy	.6945

Appendix B: **Machine Learning Code**

R code for machine learning analyses can be found here: https://osf.io/xuz8d/