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**The Role of Medication in Reducing the Negative Effects of Hyperactivity-Inattention on Achievement: A Population-based Longitudinal Investigation of Students and their Classrooms**

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## Abstract

The present study investigated the role of psychostimulants (methylphenidate, dexamphetamine; prescribed to study participants for diagnosed attention-deficit/hyperactivity disorder; ADHD) in reducing the negative effects of hyperactivity-inattention (H-I) on achievement through elementary school. Whereas the bulk of research investigating H-I and medication has focused on students (conducting student-level analyses), research into classroom climates and processes suggests this issue be examined at both student- and classroom-levels. The sample comprised 54,165 Australian students (from 5,419 classrooms) for whom H-I data were available in kindergarten and achievement data were available in year 3 and year 5. In preliminary variance components analyses, findings showed there was notable variation in H-I and psychostimulant status from classroom to classroom. In multilevel path analysis, at both student- and class-levels psychostimulants reduced the negative effects of H-I on student achievement, to a level where H-I had no significant negative impact on achievement. These effects were not moderated by dosage or psychostimulant type. Taken together, our findings add to the body of effective multi-modal educational and psychological interventions used to enhance the achievement outcomes of individual students who present with ADHD and—of particular note and novelty in this study—the classrooms to which they belong


**Keywords:** hyperactivity; inattention; psychostimulants; attention-deficit/hyperactivity disorder (ADHD); achievement; students; classrooms

**The Role of Medication in Reducing the Negative Effects of Hyperactivity-Inattention on Achievement: A Population-based Longitudinal Investigation of Students and their Classrooms**

It is well established that hyperactivity and inattention (H-I; major symptoms in disorders such as attention-deficit/hyperactivity disorder, ADHD) have negative effects on students' academic and developmental outcomes (Barkley, 2006a, 2006b; Purdie, Hattie, & Carroll, 2002). Pharmacological intervention can significantly reduce this negative effect (Vaughan, Roberts, & Needelman, 2009). Whereas the bulk of research investigating H-I and medication has focused on students (i.e., these studies conduct student-level analyses), research into classroom climates and processes suggests numerous reasons why it is critical to also examine these issues at the classroom level. First, when students are nested within classrooms, their classroom becomes potentially differentiated from other classrooms, and the behaviors and outcomes of its students and the class itself both influence and are influenced by the classroom membership (Goldstein, 2003; Marsh et al., 2012). Researchers have thus emphasized the importance of understanding group (e.g., classroom) processes. Second, it is not uncommon for classrooms to comprise more than one student who presents with H-I or is prescribed psychostimulant medication. Third, H-I can comprise externalizing behaviors that can disrupt classroom outcomes (Barkley, 2006a, 2006b). Fourth, prescription of psychostimulants for treating symptoms such as H-I is increasing in Western contexts (e.g., Boland, Galvin, Reulbach, Motterlini, Kelly, Bennett, & Fahey, 2015; Fairman, Peckham, & Sclar, 2017; Morkem, Patten, Queenan, & Barber, 2017; Salmelainen, 2002). Fifth, teachers (and schools) are increasingly held to account for their class's achievement (Harris, 2011; Lingard, Thompson, & Sellar, 2016).

Taken together, given the potentially numerous student- and class-level factors and processes implicated in H-I, the present study investigated the role of psychostimulant medication (the most frequently administered medication for H-I symptoms; Vaughan et al., 2009) in reducing the negative effects of H-I on achievement. Accordingly, the first major aim of the present study was to ascertain between-class variation in H-I and psychostimulant use (i.e., prescribed to students in the class diagnosed with ADHD). To the extent there is between-class variation in H-I and psychostimulants, it is conceivable that these both negatively affect class-average achievement. The second major aim of the present study was to investigate the unexplored role of class-average psychostimulant status in reducing the effects of class-average H-I (i.e., the interaction between class-average psychostimulants and H-I) on class-average achievement in year 3 and in year 5 (Figure 1 demonstrates). We assess these issues among a whole population-based cohort of elementary school students and then for a subset of students matched for their levels of H-I.

## Hyperactivity, Inattention, and Academic Difficulty

It is estimated that 3–5% of children are diagnosed with ADHD, with a 3:1 male to female ratio (Purdie et al., 2002), but some population estimates put this higher at around 10% (Salmelainen, 2002; Woodruff, Axelrad, Kyle, Nweke, Miller, & Hurley, 2004). Hyperactivity-inattention (H-I) is a primary symptom of ADHD (Barkley, 2006a). There is a vast body of research demonstrating the academic difficulties experienced by students with ADHD and thus reviewing each work is beyond the scope of the present study (see Barkley, 2006a for a review). However, we describe some studies as indicative of the meta-analytic research and primary research into various facets of the difficulties these children face and which have particular pertinence to functioning in the classroom and tasks that children need to perform in the classroom.

With regard to academic performance, meta-analysis by Frazier, Demaree, and Youngstrom (2004) found significantly lower performance in reading, spelling, and arithmetic. Investigating specific aspects of language impairment, Frazier et al. also found children with ADHD were more likely to struggle with simple word fluency. It is thus relevant to note that Cohen, Vallance, Barwick, Im, Menna, Horodezky, and Isaacson (2000) found that children with ADHD who also experienced language impairment were more likely to have achievement difficulties than their ADHD counterparts without language impairment. There are also impairments in verbal working memory. For example, Lorch and colleagues (2000, 2004) found significantly impaired story comprehension (that requires working memory and organization of verbal information) for children with ADHD. In terms of time management, children with ADHD have been found to have difficulty discriminating between time intervals (e.g., between very short time intervals and longer time intervals; Smith Taylor, Rogers, Newman, & Rubia, 2002). When asked to complete a set of sequenced tasks in order (without returning to a previous task), young people with ADHD showed significantly poorer planning, task scheduling, and performance monitoring (Clark, Prior, & Kinsella, 2000). In terms of emotional self-regulation, research by Braaten and Rosen (2000) found that boys with ADHD expressed less empathy and higher rates of sadness, anger, and guilt when compared to those without ADHD; further, Walcott and Landau (2004) found that children with ADHD who were frustrated in a competitive game experienced more difficulties managing their feelings. In a correlational study of high school students with ADHD, Martin (2014) found that after accounting for personal background and contextual factors, ADHD explained significant variance in schoolwork non-completion, school suspension, school expulsion, changing schools, and grade repetition.

Identifying interventions that may mitigate these academic challenges and assist the achievement of students with ADHD is critically important. One major channel of intervention is to reduce the symptomology that negatively affects academic outcomes. Thus, for example, a great deal of intervention is aimed at reducing H-I. For many years, psychostimulants have been the primary means of managing H-I (Pliszka, 2009; Vaughan et al., 2009). Accordingly, our study investigated the role of psychostimulants (prescribed to our study participants for diagnosed ADHD) in reducing the negative achievement effects of H-I. Notably, the study extends prior research (that has focused on individual students and the achievement effects of psychostimulants) to investigate the effects of both student- and class-level psychostimulant status in reducing the negative effects of student- and class-level H-I on student- and class-level achievement. Indeed, psychostimulant prescriptions are on the rise (Fairman et al., 2017) and an increasing number of students in the classroom are likely to be medicated, further underscoring the need for research into this issue at the class-level.

**Psychostimulants, Learning, and Academic Outcomes**

As noted, a pharmacological response (typically in the form of psychostimulants) is a very common mode of intervention (Barkley, 2006a, 2006b; Purdie et al., 2002; Salmelainen, 2002; Vaughan et al., 2009). Because the dopaminergic system is implicated in the pathophysiology of ADHD and its H-I symptomology (Vaidya & Gordon, 2013), medication that targets dopamine is found to be helpful in reducing H-I among children with ADHD. Psychostimulants are sympathomimetic agents that increase and enhance transmission of dopamine (and norepinephrine) in the brain. Dopamine is a neurotransmitter associated with movement and attention. In psychostimulant medicine, the therapeutic effect is achieved by steady increases of dopamine, aimed at mimicking the way dopamine is naturally produced in the brain. Recent research by Erlij and colleagues (2012) has suggested that dysfunctional signaling of dopamine in the brain is a cause of ADHD, with ADHD patients found to have an abnormal dopamine D4 receptor gene. This research has identified a network of nerve terminals (located in the basal ganglia and the thalamus) where motor activity is depressed by stimulation of dopamine D4 receptors. Thus, increasing the transmission of dopamine D4 in the thalamus and the basal ganglia may be part of the process explaining how psychostimulants reduce, for example, hyperactivity. Other recent research has suggested that use of medication can adaptively affect brain development such as normalization of grey matter volume in target brain sites (e.g., Moreno-Alcázar et al., 2016), attenuation of structural and morphological alterations that are observed in unmedicated cases (Spencer et al., 2013), and compensatory morphological changes in specific cerebellar subregions (Ivanov et al., 2014).

Research demonstrates that psychostimulant medication improves behavior, attention, and concentration (Pliszka, 2009; Purdie et al., 2002; Vaughan et al., 2009). Interestingly, there are not always direct gains in academic performance as a result of medication—suggesting that the effects of psychostimulants on achievement may be through alleviating symptoms or enhancing psycho-educational outcomes (e.g., self-esteem, self-concept, academic behaviors; Frankel, Cantwell, Myatt, & Feinberg, 1999; Rieppi et al., 2002) that are known to positively impact academic outcomes (Hattie, 2009; Marsh, 2007; see Martin 2012a for a review). As relevant to the present study, medication reduces hyperactivity and inattention (Vaughan et al., 2009) and alleviation of these symptoms better positions the student to achieve academically (Barkley, 2006a, 2006b).

## Class-level Hyperactivity-Inattentiveness and Psychostimulant Use

However, research to date (including that summarized above) has focused on individual students and the effects of psychostimulants on individual achievement. Although this has involved sample/population-based research, data are typically analyzed without regard to the groups to which these students belong. Educational researchers have demonstrated the importance of analyzing group-level effects (e.g., see Marsh et al., 2012; Martin, Bobis, Anderson, Way, & Vellar, 2011). In education, data are hierarchically structured such that, for example, students are clustered within classes. In this case, the class may be differentiated from other classes, and the students and the class as a whole both influence and are influenced by class membership (Goldstein, 2003; Muthén & Muthén, 2015; Raudenbush & Bryk, 2002).

Thus, for example, given that externalizing behavior (e.g., hyperactivity) can negatively affect other class members and their academic outcomes (DeRuvo, 2009; Lougy, DeRuvo, & Rosenthal, 2007), there is good reason for investigating class-average H-I and psychostimulant status on class-average achievement. Moreover, given prevalence rates (3-5% formally diagnosed with ADHD, Purdie et al., 2002; but up to 5-10% estimated who are undiagnosed; Woodruff et al., 2004), it is not uncommon for there to be more than one student in a class who has ADHD or who is exhibiting relatively higher H-I. Furthermore, it is possible that more than one student in a class is prescribed psychostimulants. For example, it is known that educational jurisdictions can differ in their rates of ADHD and psychostimulant use (e.g., due to availability of ADHD-specific services; socioeconomic factors; parental and familial attitudes toward health services and treatment strategies, etc.; Salmelainen, 2002) and at a population level this may also manifest in differences between classrooms.

Indeed, because teachers are increasingly held to account for their class's achievement (Harris, 2011; Lingard et al., 2016), research into factors that affect class-average achievement are not only important for class members, but also for their teacher. Indeed, even at a school level there may be unwillingness to enroll students who may reduce class-average achievement and so the present study speaks to this issue as well. Accordingly, as shown in Figure 1, we investigate the effects of both student- and class-level psychostimulant status in reducing the negative effects of student- and class-level H-I on student- and class-level achievement.

Alongside substantive and practical reasons, there are also statistical grounds for analyzing class-level H-I and psychostimulant status on class-average achievement. Single-level (or single-group) approaches can present statistical biases. Multilevel modeling is an approach that can address these biases. For example, this modeling can disentangle dependencies within groups, as well as potential confounding of within- and between-group variables (Goldstein, 2003; Raudenbush & Bryk, 2002). Thus, multilevel modeling enables a more appropriate means of evaluating hierarchical data—such as that in the present investigation.

## The Role of Moderators and Covariates

In examining our hypothesized process model (Figure 1), it is important to control for variance attributable to numerous background characteristics and also to test if any effects are moderated by medication type and dosage.

### Covariates

To identify unique variance attributable to H-I and psychostimulants, we control for factors known to be linked to or implicated in ADHD, medication status, and/or achievement. Age is one factor. For example, recent research has found younger students in a class are more likely to be prescribed psychostimulants (Whitely, Lester, Phillimore, & Robinson, 2017) and through adolescence there is a slight decline in ADHD prevalence (Barkley, 2006a, 2006b; Purdie et al., 2002). Gender is another factor, with girls tending to achieve more highly than boys (for a summary, see Martin, 2007), boys more likely to present with ADHD (Fleming et al., 2017; Purdie et al., 2002), and boys more likely to be prescribed psychostimulants (though medication prescriptions for girls are rising; Salmelainen, 2002). In regard to socioeconomic status (SES), there are positive links with achievement (Sirin, 2005) and a negative association with ADHD diagnosis (Russell, Ford, & Russell, 2015) and medication use (Simoni & Drentea, 2016). Language background may also be relevant, with Glick and Hohmann-Marriott (2007) finding that academic performance varies as a function of language background. However relationships between language background and ADHD and medication status are not well established. It is also known that ADHD is comorbid with learning disabilities (Fleming et al., 2017; Martin, 2014; Tabassam & Grainger, 2002). Finally, prior achievement is a known predictor of subsequent achievement (Hattie, 2009) and this is likely to be the case in the present study that explores longitudinal achievement patterns. Taken together, we included age, gender, English as a second language, socio-economic status (SES), disability status, and prior achievement in order to account for their influence and to better establish the unique effects of H-I and psychostimulants on achievement.

**Medication Type and Dosage**

Although methylphenidate and dexamphetamine are both psychostimulants, they are chemically different and operate on different mechanisms (and in different ways) in the brain. In the main, there are two aspects of pharmacological action. The first is pharmacokinetic that refers to the medicine's route of administration (e.g., oral), speed of release, and metabolism (how it is activated; Chandler, 2010). The second is pharmacodynamics that refers to what the medicine does when it arrives at its target (Chandler, 2010). Both methylphenidate and dexamphetamine have commercial forms that are broadly similar in terms of pharmacokinetic action. It is more in their pharmacodynamics that they differ. Methylphenidate, for example, blocks the dopamine transporter. The dopamine transporter recovers released dopamine from the synapse and deactivates it. This has the effect of accumulating dopamine in the synapse. As dopamine accumulates, it remains active and stimulates dopamine receptors pre- and post-synaptically (Chandler, 2010). Dexamphetamine increases dopamine release. It gets taken up by the dopamine transporter and competes with dopamine for reuptake (thus less dopamine is removed from the synapse) and also causes a release of dopamine (Chandler, 2010). As to their respective effectiveness, because clinicians strive to map the appropriate medicine to an individual child's presentation (DeRuvo, 2009; Salmelainen, 2002), it is likely that at a population level, there is not much difference in efficacy between medicines (see also Efron, Jarman, & Barker, 1997). Nevertheless, for completeness in subsidiary analyses, we examine whether the effects of psychostimulants on H-I and achievement are moderated by medication type (methylphenidate, dexamphetamine).

It is also the case that medication dose changes (typically increasing) over the course of childhood and adolescence. As the child grows, it is common for higher doses of medication to be prescribed to gain the same therapeutic effect (Chandler, 2010; Pliszka, 2009; Salmelainen, 2002; Vaughan et al., 2009). When investigating psychostimulants, it is therefore important to understand how their effects may be moderated as a function of dosage. We therefore include dosage in subsidiary analyses to determine if it affects the impact of psychostimulant effects on H-I and achievement. However, because dosage is adjusted as the child develops (to maintain the same level of therapeutic effectiveness across time) and because dosage levels between methylphenidate and dexamphetamine tend to be about the same (Salmelainen, 2002), we envisage it is unlikely to significantly feature in moderation findings.

## Aims of the Present Study

The present study investigated the role of psychostimulants (methylphenidate, dexamphetamine; prescribed to study participants for diagnosed ADHD) in reducing the negative effects of hyperactivity-inattention (ADHD's primary symptomology) on achievement. The first major aim of the study was to ascertain variation in H-I and psychostimulant use from classroom to classroom. To the extent there is between-class variation in H-I and psychostimulant status, it is also conceivable that these both negatively affect class-average achievement. Thus, alongside student-level modeling of H-I and psychostimulants, the second major aim of the present study was to investigate the unexplored role of class-average medication (psychostimulant) in reducing the effects of class-average H-I on class-average achievement in year 3 and in year 5 (see Figure 1). We conducted these analyses for the total sample and also for a sub-sample of medicated and non-medicated students who were comparable in H-I levels. In subsidiary analyses, we also tested the indirect effects of H-I and psychostimulants on year 5 achievement via year 3 achievement and also examined whether effects in the hypothesized model (Figure 1) are moderated by psychostimulant type (methylphenidate, dexamphetamine) and dosage.

## Methods

### Sample and Procedure

The sample comprised a 2009 cohort of 54,165 kindergarten students in New South Wales (NSW; the most populous state in Australia) whose achievement data from national testing were collected in year 3 (in 2012) and year 5 (in 2014). These students were from 5,419 classrooms (located in 2,777 government schools; the largest school sector in Australia) whose H-I was rated by teachers in kindergarten and for whom psychostimulant records (see description of our psychostimulant database below) were available over the span of the study period (up to and including 2014)[1].

A total of 1,001 (1.8%) students had been prescribed psychostimulants for treatment of diagnosed ADHD across the entire testing period (prior to the year 3 test and in the period between the year 3 test and the year 5 test). The NSW Stimulant Notification Subsystem captures information on prescriptions written for psychostimulant drugs for the treatment of ADHD that are required to be notified to the NSW Ministry of Health. These notifications are made by prescribers who are authorized to prescribe psychostimulant drugs for the treatment of ADHD (i.e., specialists). Thus, the students in our study who were prescribed psychostimulants have formally diagnosed ADHD. This study’s prescription rate is comparable to other population-based studies in Australia (e.g., 1.9%; Whitely et al., 2017). The majority of prescriptions were for methylphenidate (84%), with 16% for dexamphetamine. The average dose for methylphenidate was 24mg (*SD* = 8.78). The average dose for dexamphetamine was 19mg (*SD* = 7.73). As described below, H-I is scored by the teacher on a continuous 0-10 scale (higher scores reflecting higher H-I) and thus is not a binary variable with clinical cut-offs against which we can report who is or is not H-I. Australian Early Development Census (AEDC) does calculate a "vulnerability" H-I variable that represents students in the top 10% of H-I scores. Although this also has no formal clinical determination, it is noteworthy that those in the vulnerable group are significantly ($p < .001$) higher in psychostimulant prescription, and significantly ($p < .001$) lower in year 3 and year 5 achievement.

Just under fifty per cent of the total sample were females (49%). The mean age of participants at commencement of year 3 testing (the mid-point of the study) was 8.13 years (*SD* = .55). Around one-fifth of the participants (17%) were of non-English speaking background. A total of 3% of the sample was classified as having a learning disability. Socio-economic status (SES) was calculated based on students' home location using the Australian Bureau of Statistics Index of Relative Socio-Economic Advantage and Disadvantage. The mean was 998 (*SD* = 74), which is similar to the national mean of 1000 (*SD* = 100).

As shown in Table 1, prescription of psychostimulants for formally diagnosed ADHD was significantly ($p < .001$) associated with hyperactivity-inattention (H-I), older students, boys, English-speaking background, lower SES, presence of a learning disability, and poorer prior achievement. Table 1 also shows that higher H-I was significantly ($p < .001$) associated with boys, lower SES, presence of a learning disability, and poorer prior achievement (hence, the need to include these as covariates).

**Materials**

Four sets of variables drawn from three population datasets were the focus of this study: (1) hyperactivity-inattentiveness (H-I) from the AEDC, (2) psychostimulant prescriptions for diagnosed ADHD from the (New South Wales, Australia) Pharmaceutical Drugs of Addiction System (Non-Methadone Subsystem and Stimulant Notification Subsystem), (3) numeracy and literacy achievement from the National Assessment Program in Literacy and Numeracy (NAPLAN; Australian Curriculum, Assessment, and Reporting Authority—ACARA, 2014), and (4) socio-demographics and prior achievement also from the AEDC. Means, standard deviations, and preliminary bivariate correlations are provided in Table 1 for all student- and class-level variables.

**Hyperactivity-Inattentiveness (H-I).** For this measure we used H-I data collected in the 2009 round of the AEDC. The AEDC is a cross-sectional, population assessment of children's development at school entry. It is closely based on the Canadian Early Development Instrument (EDI; Brinkman, Gregory, Goldfeld, Lynch, & Hardy, 2014; Brinkman, Silburn, Lawrence, Goldfeld, Sayers, & Oberklaid, 2007) and cross-country research has demonstrated high consistency in the psychometric properties of the AEDC and the EDI (Janus, Brinkman, & Duku, 2011). The AEDC shows sound reliability (e.g., Janus et al., 2011), correlations with target factors in hypothesized directions, and accurate prediction of later academic and personal development (e.g., Brinkman et al., 2007, 2014). The AEDC has involved over 96% of all Australian kindergarten students (AEDC, 2014). Participants underwent an assessment for the AEDC between three and six months after school entry in 2009.

The assessment is conducted by classroom teachers for each student in the class. Whereas this methodology may limit reliability or validity for many other research studies, we suggest teacher H-I report is a valid means of data collection because: (a) teacher report continues to be a primary basis for ADHD diagnosis (e.g., Willoughby, Gottfredson, Stifter, & Family Life Project Investigators, 2017), (b) the teacher is often the first to recognize primary symptoms (Brook, Watenberg, & Gleva, 2000), and (c) other researchers investigating AEDC constructs (including H-I) have provided evidence of validity by linking the variables with other well-established aligned measures (e.g., Brinkman et al., 2007). As noted above, students had been at school for at least three months (with most between three and six months) at the time teachers assessed them and thus teachers will have developed a good basis upon which to score them.

H-I refers to students' incapacity to pay attention, follow instructions, sit still, stick to an activity, and control impulses (e.g., Would you say this child: "Can't sit still, is restless?", "Is distractible, has trouble sticking to any activity?", "Is impulsive, acts without thinking?", "Is inattentive?", 6 items; AEDC, 2012, 2014). H-I was scored from 0 to 10 such that a higher score represents higher H-I. The class-average H-I variable was generated from the student-level H-I variable using the M*plus* (Muthén & Muthén, 2015) cluster mean command. Although H-I is comprised of several items, its overall mean score is the only information made available to researchers. We thus cannot separate hyperactivity from inattention and recognize this as one of the trade-offs (relative to the numerous advantages around sampling, generalizability, representativeness, etc.) for using a secondary dataset. Also, the AEDC H-I measure is not an ADHD assessment scale. H-I is one of 16 subdomains of the AEDC instrument, with teachers assessing and recording information on nearly 100 characteristics for each child. Thus, although our psychostimulant data (described below) formally indicate ADHD status, the AEDC H-I score is a measure of teacher-appraised hyperactivity and inattention that is used to assess all kindergarten children in NSW. In line with previous research, we employed the H-I mean score in our analyses (e.g., Brinkman et al., 2007, 2014; Janus et al., 2011). Given H-I stems from a single mean score, we were unable to calculate Cronbach's alpha. Nonetheless, the reliability has been established in previous Australian research. For example, data from over 30,000 Australian children demonstrated high reliability for H-I ($\alpha$ = .91; Janus et al., 2011).

**Psychostimulant Status.** Psychostimulant prescription records were drawn from the New South Wales (Australia) Pharmaceutical Drugs of Addiction System (Non-Methadone Subsystem and Stimulant Notification Subsystem). These records identify authorizations given to medical practitioners to prescribe psychostimulants to children and young people (under the age of 16 years) diagnosed with ADHD. Two psychostimulants are indicated in these records: methylphenidate and dexamphetamine. In analyses described below, we found no notable difference in effects as a function of the two psychostimulants and so we aggregated them to form an overall indicator of psychostimulant status prior to and during the literacy and numeracy testing period. Student-level psychostimulants were indicated using effect coding (-1 = no psychostimulants; 1 = psychostimulants). Class-average psychostimulant status was generated from the student-level psychostimulant variable using the M*plus* (Muthén & Muthén, 2015) cluster mean command. Thus, low/no psychostimulant classrooms were those where there was very little or no prescription of psychostimulants. In subsidiary analyses we explored the effects of medication type (methylphenidate or dexamphetamine) and dosage (milligrams) as moderators. Class-average medication type and dosage variables were generated from the student-level medication type and dosage variables using the M*plus* (Muthén & Muthén, 2015) cluster mean command.

**Achievement:** Academic achievement was obtained from the national standardized tests—NAPLAN—administered by ACARA (2014). NAPLAN assesses student achievement in literacy (reading, writing, language conventions) and numeracy. Although NAPLAN is administered to students in all schools, our access was limited to NAPLAN results from government schools (the largest education sector in NSW and Australia). In the current study, we had access to students' year 3 (2012) and year 5 (2014) achievement. The NSW Centre for Health Record Linkage carried out record linkage across the AEDC and NAPLAN datasets, in accordance with NSW privacy guidelines. The literacy achievement score comprised reading (comprehension and interpretation of language conventions), writing (persuasive/narrative writing in relation to several criteria, such as use of accurate writing conventions, relevance of writing, range and precision of vocabulary, cohesion, and structure), and language conventions (spelling, grammar and punctuation) (National Assessment Program, 2016). The numeracy achievement score comprised algebra, measurement and geometry, statistics, probability, area, and problem solving (National Assessment Program, 2016). For each dimension, students receive a mean score. Students' average scores were from 0 to 1000, with year 3 students typically scoring around 400 and year 5 students typically scoring around 500 (ACARA, 2014). NAPLAN scores can be equated over time such that results from different years (as well as year 3 and year 5 scores) can be compared (ACARA, 2014). As our study is domain general (not assessing H-I in a particular subject domain), we employed an overall achievement score that was the aggregate of their literacy and numeracy scores. Reliability for this achievement score was high, year 3 $\alpha$ = .91, year 5 $\alpha$ = .91. The class-average achievement variable was generated from the student-level achievement variable using the M*plus* (Muthén & Muthén, 2015) cluster mean command.

**Socio-educational covariates.** Six characteristics were drawn from the AEDC data and included as covariates in the modeling. These were gender (coded 0 for males, 1 for females), age (continuous measure), language background (coded 0 for speaks English at home and 1 for speaks another language at home), SES (higher scores represent higher SES), learning disability status (coded 0 for no learning disability and 1 for a learning disability), and prior achievement (a student's kindergarten teacher's assessment of their language and cognitive functioning). For each of these variables, a class-average socio-educational variable was generated from the student-level socio-educational variable using the M*plus* (Muthén & Muthén, 2015) cluster mean command.

**Data Analysis**

Central analyses were conducted with M*plus* 7.31 (Muthén & Muthén, 2015). Maximum likelihood with robustness to non-normality was the method of estimation used (Muthén & Muthén, 2015). The M*plus* full information maximum likelihood defaults were used to deal with missing data (FIML; Muthén & Muthén, 2015). Initially, variance components analyses ascertained between-class variation in H-I, psychostimulant status, year 3 achievement, and year 5 achievement. Here, intraclass correlations (ICCs) were of main interest, which identified the percentage of between-class variance for each measure. Following this, multilevel correlation analyses were conducted. Here, in the one model, student-level (between students) associations among all variables were examined, as were all class-level (or, class-average) variables (between classes). Then, analyses centered on multilevel path analysis. In a first step of these path models, covariates and prior achievement were entered as predictors of year 3 and year 5 achievement; in a second step, student and class-average H-I, psychostimulant status, and their interaction (H-I x psychostimulants; calculated by zero-centering the main effects and finding their product; Aiken & West, 1991) were added to the first step as predictors of year 3 and year 5 achievement. We conducted analyses for the total sample and also for a sub-sample of medicated and non-medicated students who were comparable in H-I levels. We also examined indirect effects (e.g., H-I → year 3 achievement → year 5 achievement) at student- and class-levels. Figure 1 demonstrates. In subsidiary multilevel path analyses, we explored the role of dosage and psychostimulant type in potentially moderating the effects modelled in central multilevel path analyses.

In our main analyses, the overall sample size is large and this risks effects being biased towards statistical significance. Thus, Keith's (2006) guidelines were also considered—with standardized beta coefficients (β) less than .05 considered too small to be meaningful, .05 and above considered small but meaningful, .10 and above considered medium, and .25 and above considered large effects. We also report Cohen's effect size ($f^2$) for multiple *r*-square (where effect sizes of 0.02, 0.15, and 0.35 are considered small, medium, and large, respectively; Cohen, 1988).

All analyses controlled for prior achievement, gender, age, socio-economic status, language background, and learning disability at student and classroom levels. In addition, to account for the fact that students (level 1) and classrooms (level 2) in the two-level model were clustered within schools, in all analyses we adjusted standard errors for school using the "cluster" and "complex" commands in M*plus* (we did not conduct a three-level multilevel model - students nested under classrooms nested under schools - because many schools had only one classroom represented in the dataset; thus we handled clustering within school via the "complex" command).



## Results

### Classroom Variation in Hyperactivity-Inattentiveness, Psychostimulants, and Achievement

In the first set of analyses, we conducted variance components analyses to determine the between-class variation in H-I, psychostimulants, year 3 achievement, and year 5 achievement. These analyses generated intraclass correlations (ICCs) that reflect the percentage variance for these measures from class to class. ICCs for the study's key variables were: H-I = .17 (17%), psychostimulant prescription = .09 (9%), year 3 achievement = .23 (23%), and year 5 achievement = .24 (24%). It is thus clear there is notable variation between classrooms in levels of H-I, psychostimulant status, and achievement—supporting the rationale for multilevel modeling (at student and class levels) when investigating the role of psychostimulants in reducing the negative effects of H-I on achievement.

**Multilevel Correlations**

Table 1 presents multilevel correlations. These provided a first insight into key relationships to be modeled. Here the focus was on the substantive variables (H-I, psychostimulants, year 3 achievement, year 5 achievement), however their relationship with covariates (age, gender, etc.) was also included in Table 1. At the student level: H-I was positively correlated with psychostimulants ($r$ = .23, $p$ < .001), and negatively correlated with year 3 achievement ($r$ = -.34, $p$ < .001) and year 5 achievement ($r$ = -.32, $p$ < .001); psychostimulants were negatively correlated with year 3 achievement ($r$ = -.12, $p$ < .001) and year 5 achievement ($r$ = -.12, $p$ < .001). At the classroom level: class-average H-I was positively correlated with psychostimulants ($r$ = .22, $p$ < .001), and negatively correlated with class-average year 3 achievement ($r$ = -.38, $p$ < .001) and class-average year 5 achievement ($r$ = -.36, $p$ < .001); class-average psychostimulant status was negatively correlated with class-average year 3 achievement ($r$ = -.18, $p$ < .001) and class-average year 5 achievement ($r$ = -.20, $p$ < .001).

**Multilevel Path Analyses**

**Direct Effects for Year 3 Achievement.** We then explored the central hypothesized model (see Figure 1). As described in Method, these comprised two steps: the first step entered covariates and prior achievement as predictors of year 3 and year 5 achievement; the second step added H-I, medication, and their interaction as predictors. All findings are presented in Table 2, but here we focus on the results for the final step. The full set of predictive factors explained 40% of the variance in Year 3 achievement at the student-level, and 47% of the variance in Year 3 achievement at the class-level[2]. Multilevel path analysis showed that student-level H-I (β = -.10, $p$ < .001;

medium effect size, as per Keith, 2006) and psychostimulants (β = -.06, $p < .001$; small effect size) predicted lower year 3 achievement, while class-average psychostimulant rates (β = -.15, $p < .001$; medium effect size) predicted lower class-average year 3 achievement. At both student-level (β = .04, $p < .001$; small effect size) and class-level (β = .21, $p < .001$; medium effect size), there was a significant H-I x psychostimulant interaction effect for year 3 achievement. Figure 2 summarizes central substantive relationships. Table 2 shows all significant and non-significant effects. Table 2 also shows multiple *r* square (proportion of variance explained by the predictor set), and Cohen's effect size for multiple r square ($f^2$). Using Cohen's benchmarks (where effect sizes of 0.02, 0.15, and 0.35 are considered small, medium, and large, respectively; Cohen, 1988), the role of the predictor set in explaining variance in outcomes is considered a large effect size (all effect sizes > .35).

Follow-up simple effects tests at the student-level showed that H-I had a significant negative effect on achievement for the no-psychostimulant students (β = -.10, $p < .001$; medium effect size), but a non-significant (positive) effect of H-I on achievement for students prescribed psychostimulants (β = .05, $p = .15$). Follow-up simple effects tests at the class-level showed that class-average H-I had a significant negative effect on class-average achievement for the no/low-psychostimulant classrooms (β = -.09, $p < .001$; small effect size), but a non-significant effect of class-average H-I on class-average achievement for classrooms where more students were prescribed psychostimulants (β = -.05, $p = .22$).

**Direct Effects for Year 5 Achievement**. The full set of predictive factors (i.e., step 2) for year 5 achievement explained 82% of the variance at the student-level, and 86% of the variance at the class-level. This escalation in explained variance between year 3 and year 5 is largely due to the auto-regression effect of year 3 achievement predicting year 5 achievement. When considering year 5 achievement, modeling showed that student-level year 3 achievement significantly predicted student-level year 5 achievement (β = .85, $p < .001$; large effect size) and class-level year 3 achievement significantly predicted class-level year 5 achievement (β = .85, $p < .001$; large effect size). However, there were no salient direct effects between student- and class-level H-I, psychostimulants, and their interaction on year 5 achievement (see Figure 2 and Table 2). Instead, student- and class-level H-I, psychostimulants, and their interaction were more predictive of year 5 achievement via year 3 achievement (see below).

**Indirect Effects (Predicting Year 5 Achievement via Year 3 Achievement).** Table 3 demonstrates the indirect effects of H-I and psychostimulants on Year 5 achievement via Year 3 achievement. For indirect effects at the student-level: H-I predicted lower year 5 achievement via lower year 3 achievement ($\beta = -.08$, $p < .001$; small effect size), psychostimulants predicted lower year 5 achievement via lower year 3 achievement ($\beta = -.05$, $p < .001$; small effect size), and the interaction between H-I and psychostimulants on year 5 achievement via year 3 achievement was also significant ($\beta = .04$, $p < .001$; though, < small effect size). Follow-up simple effects tests showed that H-I had a negative effect on year 5 achievement via year 3 achievement for no-psychostimulant students ($\beta = -.08$, $p < .001$; small effect size) but a non-significant (positive) H-I effect on year 5 achievement via year 3 achievement for students prescribed psychostimulants ($\beta = .04$, $p = .15$).

For indirect effects at the class-level: class-average psychostimulant levels predicted lower year 5 achievement via lower year 3 achievement ($\beta = -.13$, $p < .001$; small effect size), and the interaction between class-average H-I and class-average psychostimulant use on class-average year 5 achievement via class-average year 3 achievement was also significant ($\beta = .18$, $p < .001$; medium effect size). Follow-up simple effects tests showed that class-average H-I had a negative effect on class-average year 5 achievement via class-average year 3 achievement for no/low-psychostimulant classrooms ($\beta = -.08$, $p < .001$; small effect size) but a non-significant class-average H-I effect on class-average year 5 achievement via class-average year 3 achievement for classrooms where relatively more students were prescribed psychostimulants ($\beta = -.05$, $p = .22$). Table 3 demonstrates.

**Analyses for Medicated and non-Medicated Students Comparable in H-I**

We then selected out the group of non-psychostimulant students whose H-I was comparable to the group of psychostimulant students (this sub-sample was +/- 1 *SD* [3.09] of the psychostimulant group H-I mean [4.88]). Thus, alongside the 1,001 students prescribed psychostimulants, were 10,879 students not prescribed psychostimulants but who were comparable in H-I scores. We then explored the central model (see Figure 1) for these students comparable in H-I. We describe these findings in the text below (tables and figures are only presented for the main analyses above).

**Direct Effects for Year 3 Achievement.** Multilevel path analysis showed that student-level H-I ($\beta = -.03$, $p < .01$; though, < small effect size) and psychostimulants ($\beta = -.08$, $p < .001$; small effect size) predicted lower year 3 achievement, while class-average psychostimulants ($\beta = -.21$, $p < .001$; medium effect size) predicted lower class-average year 3 achievement. At both student-level ($\beta = .03$, $p < .01$) and class-level ($\beta = .19$, $p < .001$), there was a significant H-I x psychostimulant interaction effect for year 3 achievement.

Follow-up simple effects tests at the student-level showed that H-I had a significant negative effect on achievement for the no-psychostimulant students ($\beta = -.03$, $p < .01$; though, < small effect size), but a non-significant (positive) effect of H-I on achievement for the students prescribed psychostimulants ($\beta = .05$, $p = .15$). Follow-up simple effects tests at the class-level showed that class-average H-I had a significant negative effect on class-average achievement for the no/low-psychostimulant classrooms ($\beta = -.10$, $p < .001$; small effect size), but a non-significant effect of class-average H-I on class-average achievement for classrooms where more students were prescribed psychostimulants ($\beta = -.05$, $p = .22$).

**Direct Effects for Year 5 Achievement** When considering year 5 achievement, modeling showed that student-level year 3 achievement significantly predicted student-level year 5 achievement ($\beta = .83$, $p < .001$; large effect size) and class-level year 3 achievement significantly predicted class-level year 5 achievement ($\beta = .87$, $p < .001$; large effect size). There was a statistically significant direct effect on year 5 achievement for student-level H-I ($\beta = -.02$, $p < .01$;

though, < small effect size) and psychostimulants ($\beta = -.02$, $p < .01$; though, < small effect size), but not for their interaction. Instead, the student- and class-level H-I x psychostimulant interaction had a statistically significant effect on year 5 achievement via year 3 achievement (see below).

**Indirect Effects (Predicting Year 5 Achievement via Year 3 Achievement).** For indirect effects at the student-level: H-I predicted lower year 5 achievement via lower year 3 achievement ($\beta = -.02$, $p < .01$; though, < small effect size), psychostimulants predicted lower year 5 achievement via lower year 3 achievement ($\beta = -.07$, $p < .001$; small effect size), and the interaction between H-I and psychostimulants on year 5 achievement via year 3 achievement was also significant ($\beta = .02$, $p < .01$; though, < small effect size). Follow-up simple effects tests showed that H-I had a negative effect on year 5 achievement via year 3 achievement for no-psychostimulant students ($\beta = -.02$, $p < .01$; though, < small effect size) but a non-significant (positive) H-I effect on year 5 achievement via year 3 achievement for students prescribed psychostimulants ($\beta = .04$, $p = .15$).

For indirect effects at the class-level: class-average psychostimulant levels predicted lower year 5 achievement via lower year 3 achievement ($\beta = -.18$, $p < .001$; medium effect size), and the interaction between class-average H-I and class-average psychostimulants on class-average year 5 achievement via class-average year 3 achievement was also significant ($\beta = .16$, $p < .001$; medium effect size). Follow-up simple effects tests showed that class-average H-I had a negative effect on class-average year 5 achievement via class-average year 3 achievement for no/low-psychostimulant classrooms ($\beta = -.09$, $p < .001$; small effect size) but a non-significant class-average H-I effect on class-average year 5 achievement via class-average year 3 achievement for classrooms where relatively more students were prescribed psychostimulants ($\beta = -.05$, $p = .22$).

### Subsidiary Analyses for the Effects of Dosage and Medication Type

Finally, for the sub-sample of students prescribed psychostimulants, we conducted subsidiary analyses exploring the effects of dosage and psychostimulant type (methylphenidate or dexamphetamine) on achievement. Analyses again employed multilevel path analysis. Student and class-average H-I, dosage, psychostimulant type, and the interaction of these three main effects (calculated by zero-centering the main effects and finding their product; Aiken & West, 1991) were modeled as predictors of year 3 and year 5 achievement. All analyses controlled for prior achievement, gender, age, socio-economic status, language background, and learning disability. In addition, year 3 achievement was included as a predictor of year 5 achievement. At the student-level, dosage, psychostimulant type, and their interaction with H-I did not significantly predict year 3 achievement or year 5 achievement. At the class-level, class-average dosage, class-average psychostimulant type, and their interaction with class-average H-I did not significantly predict class-average year 3 achievement or class-average year 5 achievement. Table 4 summarizes findings.

## Discussion

The present findings showed there is notable variation in hyperactivity-inattention (H-I) and psychostimulants (prescribed to study participants with diagnosed ADHD) from classroom to classroom. Consistent with prior research, psychostimulants reduced the negative effects of H-I on student achievement, to a level where H-I had no significant impact on achievement. The more novel aspect of the study showed that class-average psychostimulant levels reduced the negative effects of class-average H-I on class-average achievement, to a level where class-average H-I had no significant impact on class-average achievement. Another distinguishing feature of the study was the demonstration that student and class-average H-I and psychostimulant effects impacted year 5 achievement via year 3 achievement. Moreover, the study’s effects were not moderated by dosage or psychostimulant type and were sustained when a sub-sample of medicated and non-medicated students with comparable levels of H-I were investigated. Finally, although psychostimulants reduced the negative effects of H-I on achievement, as a main effect the impact of psychostimulants on achievement was negative. This suggests that psychostimulants are not a means of increasing achievement per se; instead their effectiveness appears to be specific to students higher in H-I. We conclude that alongside effective educational and psychological intervention for students with high levels of H-I (DeRuvo, 2009; Lougy et al., 2007; Purdie et al., 2002), our findings have significant implications for practitioners in their efforts to enhance the achievement outcomes of individual students who present with H-I and the classrooms to which they belong. Indeed, the latter finding is a particularly unique yield of the present study.

**Findings of Particular Note**

The first focus for analyses centered on ascertaining the extent to which H-I and psychostimulant levels varied across classrooms. Whereas the bulk of research to date has centered on students and student-level analyses, researchers have shown that when students are nested within classrooms, their class becomes potentially differentiated from other classes, and its members and the class itself both influence and are influenced by classroom membership (Marsh et al., 2012; Martin et al., 2011). Thus, most researchers have conducted research into ADHD and its H-I symptomology without sufficient regard to the groups to which they belong and the extent to which these groups themselves are differentiable to an extent that has relevance to H-I and its management[3]. It was therefore notable to find substantial variation from class to class in H-I (17%) and also around 10% variation in psychostimulants from class to class. Not only does this suggest a greater need for multilevel modeling (at student and class levels) when investigating ADHD and H-I, it also has important practical implications in terms of the levels (student and classroom) at which to direct intervention (discussed below).

Consistent with a vast body of prior research, the study found that student-level H-I was associated with lower subsequent achievement. The academic difficulties associated with H-I are well documented (Barkley, 2006a, 2006b; Fleming et al., 2017; Martin, 2014; Pliszka, 2009; Purdie et al., 2002). However, whereas most prior research tends to be sample-based, our research was large-scale and population-based, thereby providing quite a robust test of the role of H-I in students' academic achievement. Moreover, these H-I effects were beyond the roles played by socio-demographics, learning disability status, and even prior achievement and thus demonstrate that H-I is indeed an impediment to students' academic development and critical to address in order for a child to achieve to potential. Furthermore, given an estimated 3-5% ADHD prevalence (Purdie et al., 2002; but see higher population estimates, Salmelainen, 2002; Woodruff et al., 2004) and that only 1.8% of our sample was prescribed medication (consistent with other national estimates in Australia; Whitely et al., 2017), it is clear there were many children who were symptomatic but not medicated. It is thus noteworthy that our findings showed that those scoring relatively higher on H-I and on medication reflected better achievement than unmedicated students also scoring relatively higher on H-I. Indeed, whereas much prior research into medication and student outcomes tends to be sample-based, our research drew on all prescription records in the state for government school students and linked them to achievement across time. Although the present study did not focus on reduction of symptoms per se (this is well documented elsewhere; Pliszka, 2009; Vaughan et al., 2009), it did show that medication moderated the effects of H-I on subsequent achievement.

Another major finding from this study was the role of class-average psychostimulant status in moderating the negative effects of class-average H-I on class-average achievement. Given that externalizing behavior (e.g., hyperactivity) can negatively affect other class members and their academic outcomes (DeRuvo, 2009), it is of significant note that we identified one approach to reducing the negative effects of class-average H-I. Moreover, as discussed earlier, because teachers and schools are increasingly held to account for class-average achievement (Harris, 2011; Lingard et al., 2016), research into factors that affect class-average achievement are not only important for class members, but also for their teacher. This has significant implications for interpreting class-level achievement and also for practical approaches to enhancing whole-class outcomes (discussed below).

Another notable finding was revealed through the indirect effects. Although the moderating role of psychostimulants did not directly impact year 5 achievement, it did play a part via year 3 achievement. Specifically, psychostimulants reduced the negative H-I effects on year 3 achievement that in turn positively predicted year 5 achievement. In some ways this is consistent with prior research that has suggested the short-term yields of psychostimulants tend to be more evident than long-term yields (Rieppi et al., 2002) and that the evidence for short-term effectiveness tends to be stronger than evidence for long-term effectiveness (see Chandler, 2010 for review). Our findings may shed further light on this. They suggest that although medication is not directly connected to distal (year 5) achievement, it is linked indirectly (via year 3 achievement).

**Key Findings in Perspective**

A key element of the present study was the inclusion of prior variance in achievement—and the substantial role played by prior achievement in predicting subsequent achievement. There are four implications that follow from this finding. First, the findings of prior achievement on subsequent achievement confirm a very well-established educational phenomenon: among the most salient factors in how a student achieves is how he or she performed previously (Hattie, 2009). On the one hand this signals the need for direct intervention on the skills implicated in students' achievement (see practice implications below). On the other hand, it introduces a major challenge for researchers and practitioners: to identify and address factors that explain variance in achievement that impact beyond the effects of prior achievement. Indeed, prior variance (auto-regression) typically explains so much subsequent variance that identifying small to medium effects has educational merit.

This leads to a second implication: the small to medium effects (in the context of strong auto-regression effects) found with regard to H-I and medication suggest these as factors worthy of attention. Given the reality that auto-regression in achievement will almost always explain the bulk of variance in achievement, it is a reality that a diversity of other factors will contribute with small to medium effects and that these small to medium effects are often feasible additional targets for intervention. Indeed, perhaps the most novel element of this study was the investigation of class-level effects for medication and achievement and it was here that the largest effects (notwithstanding achievement auto-regression) were found. Thus, one of the most informative and illuminating effects in this study (class-level H-I, medication, etc. effects) was where all the medium effect sizes were found.

Following from this is a third implication: after accounting for prior variance in achievement in the present regression models, the predictor set is essentially predicting positive and negative residuals of achievement—or, put another way, upward and downward shifts in achievement after accounting for prior achievement. Getting gains in achievement outcomes is not an easy task (Martin, 2015a) and even small to medium effect sizes predicting achievement shifts can be educationally noteworthy (Cohen, 1988). The present analytic design is thus a powerful one in that it identified factors (H-I, medication, their interaction) that predicted positive (and negative) residuals, and thus, upward (and downward) shifts in achievement across time. This being the case, the proximal paths from H-I, medication, and their interaction to year 3 achievement is essentially predictive of gain or decline in year 3 achievement. Thus, even though H-I, etc. did not directly predict more distal year 5 achievement, the fact they predicted year 3 achievement is no trivial effect.

A fourth further point on these findings is to recognize that medication and H-I predated the year 3 and year 5 achievement measures and were likely impacting achievement outcomes well before the year 3 and year 5 tests were conducted. Thus, H-I and medication not only directly impact year 3 achievement, but also prior achievement that impacts year 3 achievement. To provide one insight into this we can look at the Table 1 correlations between prior achievement (i.e., achievement preceding year 3 and year 5 tests) and students' H-I and medication status. These correlations are significant and suggest that H-I and medication impact year 3 achievement not only by way of their direct effect on year 3 achievement, but also in terms of the variance they share with prior achievement that predicts year 3 achievement.

Our findings also offer a cautionary note. At student- and class-levels, psychostimulants were negatively associated with subsequent achievement. This is not surprising given that psychostimulants have been prescribed for a condition known to substantially impede academic achievement (Martin, 2012a). Unfortunately, even while receiving medication, children with ADHD still fare worse than their non-ADHD peers (Fleming et al., 2017). Moreover, it is estimated that psychostimulant medication is not effective for at least 10% of children with ADHD (Salmelainen, 2002). Thus, psychostimulants are not a means of enhancing achievement per se; rather, they reduce the negative impact of symptoms (in our study, H-I) on achievement. We are therefore emphatic that psychostimulants are for management of formally diagnosed conditions (and their symptoms) that have achievement-related implications. Our findings do not support (nor do we advocate) their use simply for enhancement of achievement.

**Implications for Practice**

A useful summary of intervention effectiveness is that provided in Purdie et al.'s (2002) meta-analytic research. In terms of ADHD symptoms (hyperactivity, inattention), pharmacological intervention was considered most effective, followed by non-academic intervention (e.g., social skills training, behavioral) for hyperactivity. They also make the point that cognitive and educational interventions are effective when targeting academic outcomes (not just symptomology). Thus, although our study is focused on pharmacological intervention and supports its use as part of a multi-modal response to reducing the negative effects of H-I symptoms on achievement, given ours is a multi-level investigation we also point to student- and class-level intervention as well.

Research has been important in identifying specific deficits implicated in ADHD that have direct implications for student-level intervention and for differentiating instruction where possible (Tomlinson, 1999). For example, difficulties with self-monitoring and time management (Barkley, 2006a), suggest direction for more effective use of time, including allowing breaks between tasks decreased academic workload, daily planners, and extending the time allowed on tasks and tests (Lougy et al., 2007; Martin, 2012a, 2016). Due to the burden that ADHD places on students' working memory (Lorch et al., 2000, 2004), effective educational accommodations can also include clear and concise instructions that do not tax working memory (Lougy et al., 2007). Given struggles with accessing working memory and recalling information (Barkley, 2006a), visual scaffolds (e.g., graphic organizers) can be effective (DeRuvo, 2009). Relatedly, students with ADHD can experience difficulty distinguishing important/central information from unimportant/non-central information and thus advance organizers that briefly signal this important information up-front can be helpful here (DeRuvo, 2009). Given processing speed can be slower for student with ADHD (Mayes & Calhoun, 2007), it can be difficult for them to keep up with note-taking; thus using cloze notes can assist (DeRuvo, 2009). Goal-setting is an effective strategy to boost achievement (Locke & Latham, 2002); given students with ADHD can struggle in relative achievement (i.e., compared to other students), personal best goal-setting has been suggested, with research showing personal best goals are positively associated with academic outcomes for students with ADHD (Martin, 2012b).

Given our study identified class-level effects, class-level intervention is also appropriate. Such intervention involves well-established approaches such as consistent and predictable daily and lesson routines, a relatively orderly classroom, a physical environment conducive to concentration (e.g., appropriate seating arrangements, good management of noise and visual stimuli), and proactive discipline (foreshadowing and preventing problems) rather than reactive discipline (reacting to problems) (DeRuvo, 2009; Lougy et al., 2007).

It is also important to note that (a) the present study found substantial variance in achievement explained by prior achievement (i.e., the strongest predictor of subsequent achievement was prior achievement) and (b) the direct effect of medication on achievement was negative (however, the interaction showed that medication operated to reduce symptomology such that achievement was then not impaired). Thus, in addition to intervention aimed at facilitating individual students with regard to symptomology and in addition to widely-implemented classroom interventions (see above), the study underscores the importance of educational interventions directly targeting achievement. Particularly when targeting achievement directly, researchers have recommended explicit instructional techniques—especially for students with executive function disorders such as ADHD (Martin, 2015b). Building on cognitive load theory (CLT; Sweller, 2012) to articulate specific CLT instructional processes, “load reduction instruction” (LRI) has recently been introduced as a way to appropriately scaffold students to higher achievement while appropriately managing the load on students' working memory (Martin, 2016). Martin and Evans (2018) have shown that classes in which LRI is implemented score significantly higher in academic achievement. Indeed, Martin (2016) identified LRI as an instructional approach with significant potential for directly supporting achievement for students with ADHD. Five principles underlie LRI and each is specified with a view to easing the burden on all students' working memory—and especially for students whose working memory may be disproportionately burdened, such as those with ADHD. The five principles are difficulty reduction, support and scaffolding, practice, feedforward (improvement-oriented feedback), and guided independence (Martin, 2016; Martin & Evans, 2018). The first four are well-recognized instructional approaches for students with ADHD (e.g., DeRuvo, 2009), but even the fifth element of LRI that is aimed at nurturing independence still has an explicit emphasis on guidance and scaffolding by the teacher (Mayer, 2004) and thus is in line with well-established recommendations for students with ADHD (DeRuvo, 2009).

**Limitations and Future Directions**

There are some limitations to the study that are important to consider when interpreting findings and which have implications for future research. First and foremost, although our study focused on medication, we fully recognize the role of effective educational and psychological intervention for students with ADHD (DeRuvo, 2009; Lougy et al., 2007). Medication is but one part of effective multi-modal intervention for students with ADHD (Purdie et al., 2002). In our discussion above, we outlined some of these. Second, we only had access to achievement data for students who attended government schools. Although this is by far the largest school sector in Australia, it is important to explore the present issues among students attending other types of schools. Also, we had no information on any possible student- and class-level interventions for ADHD that may have also affected H-I and subsequent achievement. Third, the use of population-level data was a strength of the study; however, secondary data sets are not purpose-designed for specific research projects. Thus, for example, we could not disentangle hyperactivity from inattentiveness using our AEDC data. Also, AEDC releases only construct-level data and so H-I was a composite variable provided by AEDC. Although the reliability and validity of AEDC constructs (including H-I) has been demonstrated before (e.g., Brinkman et al., 2007), our single-item H-I factor meant we could not conduct latent modeling (from multiple H-I items) that corrects for unreliability. Future research disentangling specific H-I constructs and using multi-item factors is needed.

Fourth, given the nature of the AEDC dataset, we only had H-I data from students in kindergarten. Although we had prescription data all the way through the study, moving forward it will be interesting to examine H-I through school. On a related note, although we had longitudinal data, the research design was correlational in nature and thus we do not make judgements about causality. Fifth, H-I was based on teacher ratings of students' behavior. We do point out, however, that because teacher report continues to be a primary basis for ADHD diagnosis, because the teacher is often the first to recognize primary symptoms (Brook et al., 2000), and because other researchers have provided evidence of AEDC construct validity by linking the variables (including H-I) with other well-established measures (e.g., Brinkman et al., 2007), teacher H-I report can be considered a valid means of data collection. Nonetheless, H-I identified here should be compared with data derived from others (e.g., parents/carers) and we emphasize that the utility of this measure is for research and early support purposes—not for ongoing labelling of the child in subsequent years. Sixth, our study comprised Australian children and thus further research is needed to ascertain the generalizability of these findings among children from other countries. Given rises in diagnosis and medication in other Western and non-Western nations (e.g., Boland et al., 2015; Fairman et al., 2017; Man et al., 2017; Morkem et al., 2017) as there has been in Australia, we suspect findings would generalize—but this is an empirical question yet to be answered. Seventh, although we focused on the most widely used medications for ADHD (psychostimulants; Vaughan et al., 2009), there are other medications used for management of ADHD symptoms that are important to investigate in classroom-level research. Finally, although our study focused on students and teachers, there is also a role for parents and allied health professionals in managing ADHD and improving educational outcomes (Purdie et al., 2002). Future research should look at these as well.

## Conclusion

Taken together, the unique status of the data (i.e., population-based linked H-I, medication, and achievement records spanning five years) and the implementation of multilevel modeling allowed quite novel insight into how student H-I and medication status may also have class-level achievement implications. Our findings thus add to the existing body of multi-modal approaches that implement student- and class-level educational and psychological interventions. In so doing, the findings have substantial relevance for practitioners in their efforts to enhance the achievement outcomes of individual students who present with H-I and—of particular note and novelty in this study—the classrooms to which they belong.

**Footnotes**

1. This study complements another cross-sectional paper that draws on the full AEDC dataset to examine anxiety and cognitive skills (Collie, Martin, Roberts, & Nassar, 2018) and another that uses person-centered analyses to examine social and emotional behavioral profiles and their links to achievement (Collie, Martin, Nassar, & Roberts, 2018).

2. Because our model was saturated (all parameters estimated) we could not generate model fit indices such as CFI, RMSEA, etc. However to provide a sense of these we estimated a model in which the direct effects of H-I, medication, and their interaction on year 5 achievement were removed in order to free up parameters and allow some indication of model fit. This yielded the following excellent model fit: chi square = 42756, df = 110, CFI = .99, RMSEA = .010, SRMR = .002.

3. However, multilevel modeling has been used to investigate clustering of children with ADHD in groups such as families and community clinics and also assessed multilevel phenomena such as intra-day variability (e.g., Epstein et al., 2014; Knouse et al., 2008; Segenreich et al., 2015).

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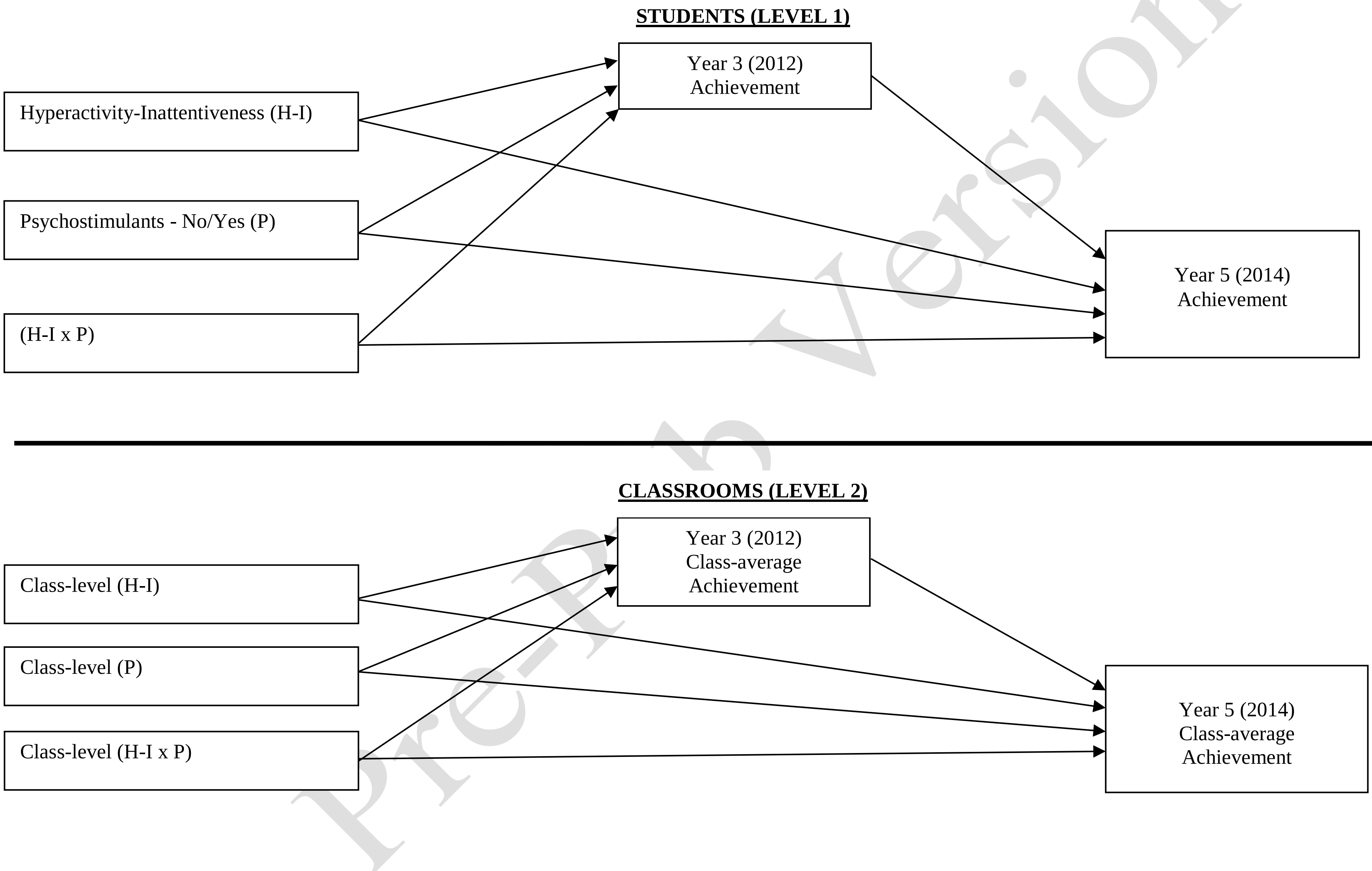




Figure 1. Hypothesized multilevel path model

Note. Model controls for age, gender, non-English speaking background (NESB), socio-economic status (SES), learning disability, and prior achievement

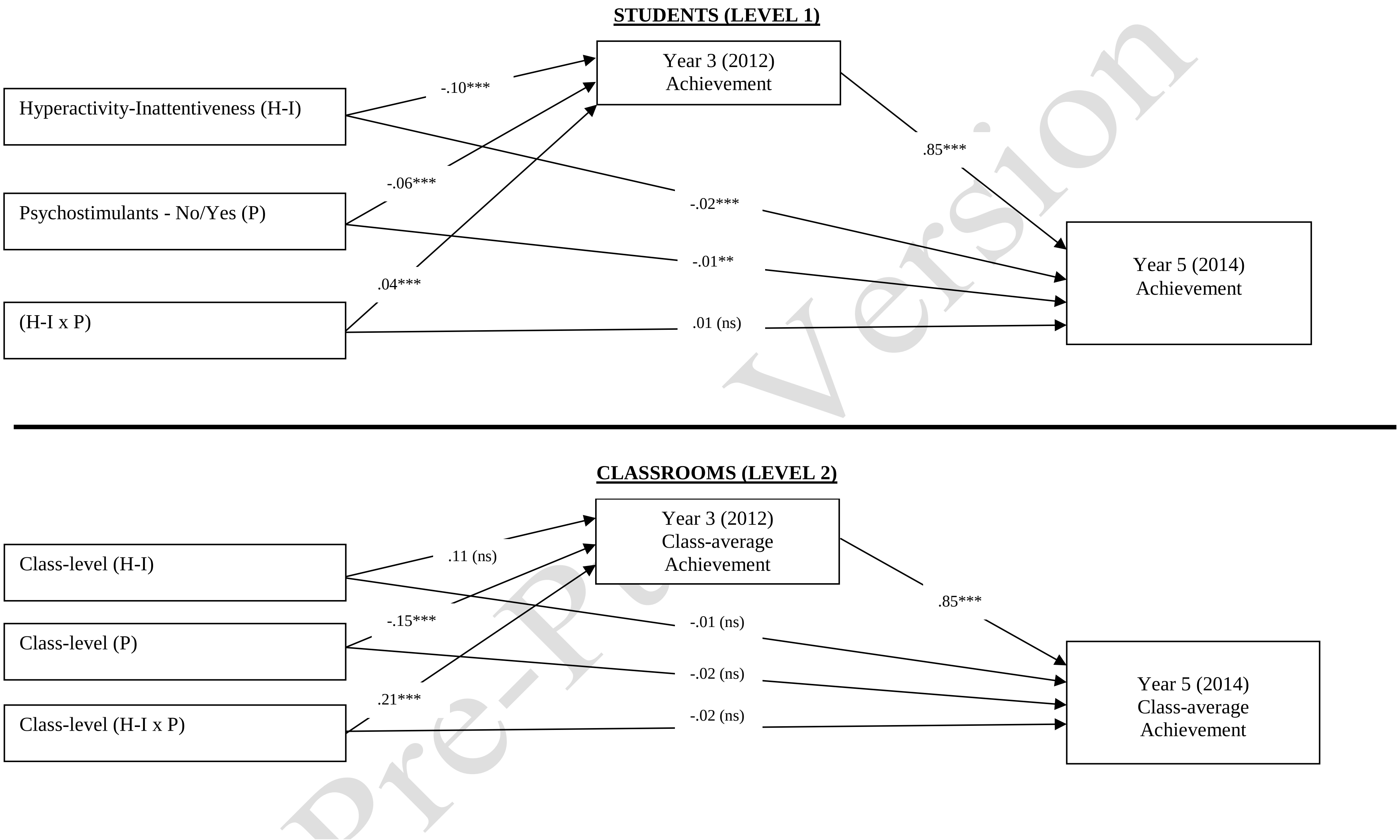



Figure 2. Predicting Year 3 and Year 5 Achievement (findings from Step 2 of Table 2) - Significant standardized beta (β) paths, controlling for age, gender, non-English speaking background (NESB), socio-economic status (SES), learning disability, and prior achievement

Notes. * *p*<.05, ** *p*<.01, *** *p*<.001; No statistically significant effects between Student (L1) and Classroom (L2) level (H-I), (P), (H-I x P) → Year 5 Achievement

Table 1. Descriptive Statistics and Multilevel Correlations

| | Descriptive Statistics | | Multilevel Correlations | | | |
|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Hyperactivity-Inattentiveness** | **Psychostimulants (Y)** | **Year 3 Achievement** | **Year 5 Achievement** |
| **LEVEL 1 (Student)** | | | | | | |
| Hyperactivity-Inattentiveness | 1.32 | 2.14 | - | | | |
| Psychostimulants (Y) | -.93 | .38 | .23*** | - | | |
| Year 3 Achievement | 412 | 74 | -.34*** | -.12*** | - | |
| Year 5 Achievement | 492 | 71 | -.32*** | -.12*** | .90*** | - |
| Age | 8.13 | .55 | .02** | .03*** | -.01 | -.03*** |
| Gender (FM) | .49 | .49 | -.23*** | -.08*** | .06*** | .04*** |
| NESB (Y) | .17 | .38 | .01 | -.05*** | .04*** | .08*** |
| SES | 998 | 74 | -.08*** | -.03*** | .30*** | .30*** |
| Learning Disability (Y) | .03 | .17 | .24*** | .11*** | -.26*** | -.25*** |
| Prior Achievement | 8.81 | 1.66 | -.44*** | -.12*** | .57*** | .54*** |
| **LEVEL 2 (Classroom)** | | | | | | |
| Class-level Hyperactivity-Inattentiveness | 1.46 | 1.41 | - | | | |
| Class-level Psychostimulants | -.92 | ..20 | .22*** | - | | |
| Class-level Year 3 Achievement | 409 | 50 | -.38*** | -.18*** | - | |
| Class-level Year 5 Achievement | 489 | 48 | -.36*** | -.20*** | .92*** | - |
| Class-level Age | 8.29 | .58 | .07** | -.01 | -.01 | .02 |
| Class-level Gender | .49 | .26 | -.25*** | -.09*** | .13*** | .11*** |
| Class-level NESB | .15 | .26 | -.01 | -.08*** | .06** | .10*** |
| Class-level SES | 995 | 71 | -.12*** | -.05** | .39*** | .41*** |
| Class-level Learning Disability | .05 | .17 | .31*** | .12*** | -.41*** | -.41*** |
| Class-level Prior Achievement | 8.59 | 1.43 | -.49*** | -.16*** | .59*** | .58*** |

* *p*<.05, ** *p*<.01, *** *p*<.001
Notes. NESB = non-English speaking background, SES = socio-economic status

Table 2. Effects on Year 3 and Year 5 Achievement

| | Step 1 | | Step 2 | |
|---|---|---|---|---|
| | **Year 3 Achievement β** | **Year 5 Achievement β** | **Year 3 Achievement β** | **Year 5 Achievement β** |
| **LEVEL 1 (Student)** | | | | |
| Age | -.01* | -.02*** | -.01* | -.02*** |
| Gender (FM) | <-.01 | -.02*** | -.02*** | -.02*** |
| NESB (Y) | .13*** | .06*** | .12*** | .06*** |
| SES | .22*** | .05*** | .21*** | .05*** |
| Learning Disability (Y) | -.05*** | -.01** | -.04*** | -.01* |
| Prior Achievement | .54*** | .05*** | .49*** | .04*** |
| Year 3 Achievement | - | .86*** | - | .85*** |
| Hyperactivity-Inattentiveness (H-I) | | | -.10*** | -.02*** |
| Psychostimulants (P) | | | -.06*** | -.01* |
| H-I x P | | | .04*** | <.01 |
| - (No Psychostimulants: H-I → Yr 3 Achieve, β = -.10, *p* < .001) | | | | |
| - (Psychostimulants: H-I → Yr 3 Achieve, β = .05, *p* = .15) | | | | |
| R Square | .38*** | .81*** | .40*** | .82*** |
| Cohen Effect Size | 0.61 | 4.26 | .0.67 | 4.56 |
| **LEVEL 2 (Classroom)** | | | | |
| Class-level Age | -.02 | .02 | -.01 | .02 |
| Class-level Gender | .02 | -.02* | .01 | -.02* |
| Class-level NESB | .14*** | .06*** | .13*** | .06*** |
| Class-level SES | .30*** | .06*** | .30*** | .07*** |
| Class-level Learning Disability | -.11*** | -.04** | -.09*** | -.04** |
| Class-level Prior Achievement | .47*** | .06*** | .42*** | .06*** |
| Class-level Year 3 Achievement | - | .85*** | - | .85*** |
| Class-level Hyperactivity-Inattentiveness (H-I) | | | .11 | -.01 |
| Class-level Psychostimulants (P) | | | -.15*** | -.02 |
| Class-level H-I x P | | | .21*** | -.02 |
| - (No Psychostimulants: H-I → Yr 3 Achieve, β = -.09, *p* < .001) | | | | |
| - (Psychostimulants: H-I → Yr 3 Achieve, β = -.05, *p* = .22) | | | | |
| R Square | .45*** | .85*** | .47*** | .86*** |
| Cohen Effect Size | .82 | 5.67 | 0.89 | 6.14 |

* *p*<.05, ** *p*<.01, *** *p*<.001

Notes. NESB = non-English speaking background, SES = socio-economic status

Table 3. Indirect Effects on Year 5 Achievement via Year 3 Achievement

| | β | *p* |
|---|---|---|
| **LEVEL 1 (Student)** | | |
| Hyperactivity-Inattention (H-I) → Year 3 Achieve → Year 5 Achieve | -.08 | <.001 |
| Psychostimulants (P) → Year 3 Achieve → Year 5 Achieve | -.05 | <.001 |
| H-I x P → Year 3 Achieve → Year 5 Achieve | .04 | <.001 |
| - No Psychostimulants: H-I → Year 3 Achieve → Year 5 Achieve | -.08 | <.001 |
| - Psychostimulants: H-I → Year 3 Achieve → Year 5 Achieve | .04 | .15 |
| **LEVEL 2 (Classroom)** | | |
| Class-level (H-I) → Class-lev Year 3 Achieve → Class-lev Year 5 Achieve | .09 | .09 |
| Class-level (P) → Class-lev Year 3 Achieve → Class-lev Year 5 Achieve | -.13 | <.001 |
| Class-level (H-I x P) → Class-lev Year 3 Achieve → Class-lev Year 5 Achieve | .18 | <.001 |
| - No Psychostimulants: Class-lev H-I → Class-lev Year 3 Achieve → Class-lev Year 5 Achieve | -.08 | <.001 |
| - Psychostimulants: Class-lev H-I → Class-lev Year 3 Achieve → Class-lev Year 5 Achieve | -.05 | .22 |

Note. Indirect effects tests control for Student (L1) and Classroom (L2) level age, gender, NESB, SES, learning disability, and prior achievement

Table 4. Psychostimulant Group Sub-analyses: Dose and Medication Type Predicting Year 3 and Year 5 Achievement

| | **Year 3 Achievement** | | **Year 5 Achievement** | |
|---|---|---|---|---|
| | **β** | ***p*** | **β** | ***p*** |
| **LEVEL 1 (Student)** | | | | |
| Year 3 Achievement | | | .79 | <.001 |
| Hyperactivity-Inattention (H-I) | .05 | .14 | .01 | .66 |
| Dose (D) | -.01 | .59 | -.04 | .05 |
| Methylphenidate (MT) | .01 | .76 | .01 | .55 |
| Dexamphetamine (DX) | .03 | .33 | -.04 | .06 |
| H-I x D | .04 | .22 | -.03 | .21 |
| H-I x MT | -.02 | .31 | .01 | .41 |
| H-I x DX | .03 | .39 | .02 | .50 |
| **LEVEL 2 (Classroom)** | | | | |
| Class-level Year 3 Achievement | - | - | .85 | <.001 |
| Class-level Hyperactivity-Inattention (H-I) | -.18 | .13 | .09 | .13 |
| Class-level Dose (D) | -.06 | .13 | -.01 | .75 |
| Class-level Methylphenidate (MT) | -.15 | .10 | -.01 | .81 |
| Class-level Dexamphetamine (DX) | -.07 | .42 | -.07 | .08 |
| Class-level H-I x D | .17 | .19 | -.08 | .26 |
| Class-level H-I x MT | -.02 | .86 | -.05 | .32 |
| Class-level H-I x DX | .25 | .05 | .05 | .15 |

Note. Analyses control for Student (L1) and Classroom (L2) level age, gender, NESB, SES, learning disability, and prior achievement