Identification Of Stimulant Misuse And Malingering Of Symptoms Of Attention Deficit Hyperactivity Disorder

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IDENTIFICATION OF STIMULANT MISUSE AND MALINGERING OF SYMPTOMS OF ATTENTION DEFICIT HYPERACTIVITY DISORDER

A Dissertation

presented in partial fulfillment of requirements

for the degree of the Doctor of Philosophy

in the Department of Pharmacy Administration

The University of Mississippi

By

Sujith Ramachandran

May 2017
ABSTRACT

It was estimated in 2013 that 54.3 million individuals reported overall lifetime prevalence of prescription drug abuse, and 16.7 million individuals reported misusing or abusing prescription drugs in the past year. This study focuses on the abuse of psychostimulants, popularly used for treatment of Attention Deficit Hyperactivity Disorder (ADHD). It is estimated that 10 to 30% of college students might be abusing stimulants, mostly for academic purposes. The incidence of stimulant related ER visits has nearly doubled in the last decade. It is also estimated that 10 to 50% of ADHD evaluations in a University setting might be exaggerated or malingered. This study, in three parts, explored the feasibility of identification of prescription stimulant abuse using large databases, developed a subtle behavioral self-reported scale, the Subtle ADHD Malingering Screener (SAMS), for use in the primary care setting to identify malingering among individuals reporting symptoms of ADHD, and compared the sensitivity of the SAMS to other existing scales. The first paper identified two latent classes in the stimulant user population based on risk factors for abuse identified from literature. The second paper developed a 10-item 2-factor screener instrument, the SAMS, with satisfactory reliability and factorial validity. The third paper calculated a cut-off score for the SAMS, and estimated a sensitivity of 90.3% and a specificity of 80.1% toward malingering of ADHD symptoms. This dissertation pursued innovative methods to help in the early identification of prescription stimulant abusers and malingerers, in order to reduce overdiagnosis of ADHD, and abuse of prescription stimulants.
## LIST OF ABBREVIATIONS AND SYMBOLS

<table>
<thead>
<tr>
<th>Abbreviation</th>
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<tr>
<td>ADHD</td>
<td>Attention Deficit Hyperactivity Disorder</td>
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<td>SAMS</td>
<td>Subtle ADHD Malingering Screener</td>
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<tr>
<td>PAI</td>
<td>Personality Assessment Inventory – Adult</td>
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<tr>
<td>LCA</td>
<td>Latent Class Analysis</td>
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<td>PDA</td>
<td>Prescription Drug Abuse</td>
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ACKNOWLEDGEMENTS

This dissertation was a project in process from the summer of 2014 to the spring of 2017. Over these two and a half years, it took a small village to complete this project, and I would be amiss if I failed to acknowledge all the help I have had. I will begin with my beloved advisor, Dr. John P. Bentley, who has been my mentor, both personally and professionally, and has been the person I would find refuge in, for all my problems. He has also been my strongest advocate and my champion while I found my profession, and for this, I will always be thankful to him. The rest of my committee, Dr. Benjamin F. Banahan, Dr. Erin Holmes, Dr. Meagen Rosenthal, and Dr. John Young. When this project was merely an idea during the summer and fall of 2014, it seemed more like a wild dream than a realistic research project, and they gave me the confidence to pursue it, and most importantly, drove me in a direction which was realistic and achievable. Without their ideas, support, and help, this dissertation would not have been feasible. I need to mention a special word of thanks to my mentor & thesis advisor, Dr. Benjamin Banahan, who has helped me grow into my own self, and find my career. I have much to learn from you, Dr. Banahan, and I thank you for being a role model for me and several other students.

During these two years, Dr. Amit S. Patel, Dr. Donna West-Strum, Dr. Dwight Wadell, Nancy Jones, Sheree Jones, and several of my fellow graduate students – Dr. Amod Athavale, Dr. Manasi Datar, Dr. Zainab Shahpurwala, Dr. Ruchit Shah, Dr. Tristen Jackson, Dr. Nagendra Punyamurthula, Kaustuv Bhattacharya, Sasi Kiran Nunna, Nilesh Gangan, and Nick Keeling – have been the sounding board for my ideas, always ready to listen, and bouncing forth ideas that
have sometimes changed the very scope of this project, molding it several times over until it reached its final form, presented here. I look forward to their friendship for several years to come.

The toughest part of this dissertation were the several challenges we had to face with regard to feasibility, data collection, resources, and logistics. The person who was most instrumental throughout this process was Dr. John Young. He has been an incredible resource, often sharing ideas that have made the seemingly impossible, incredibly reachable. Several professors, instructors, and graduate students on the campus of the University of Mississippi – Dr. Tiffany Bensen, Dr. Anne Benson, Dr. Robert Doctor, Dr. Conrad Puozza, Dr. Ahmed Rashed, Dr. Jason Ritchie, Dr. Matthew Shifflett, Dr. John Wiginton, Amy Beel, Anna Black, Marie Darden, Kristen Johnson, Brooklee Lightsey, Kelly Peck, Sarah Scott, Alex Sivvopolous, Lauren Weathers, and Sam Wilson – also helped me during the data collection and item development phase of this dissertation. Without their assistance, this project would have never seen the light of day. I sincerely thank them for their willingness to help, and wish them the best for all future endeavors.

Finally, I would like to my family for their support during the last 5 years. My mom, Radhika, my dad, Ramachandran, my sister, Sindhu, and her family, have all played bigger roles in the completion of this project than they will admit. I have much to learn from each of them, and will always be indebted to them.
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CHAPTER 1

INTRODUCTION TO PRESCRIPTION STIMULANT ABUSE: A REVIEW OF PREVALENCE, SOCIETAL IMPACT, SOURCES, AND EFFECT OF ABUSE
INTRODUCTION

Introduction to prescription drug abuse

The United States’ War on Drugs is an extensive legal, economic, and sociocultural effort to change the fact that a nation that comprises only 5% of the world’s population consumes over 25% of its illicit drugs (Zedido & Wheeler, 2012). The war on the use of illicit drugs has been mostly inefficient and ineffective, and has overshadowed the problem of abuse of prescription drugs (Zedido & Wheeler, 2012). An initial spotlight on prescription drugs was brought by the White House Conference on Prescription Drug Abuse in 1980 that pointed out the high rates of illness and death associated with misuse and abuse of prescription drugs (Wilford et al., 1994). While some efforts were made to address this issue by the White House and the American Medical Association (AMA), the problem has only grown worse (Wilford et al., 1994). In 2011, the Office of National Drug Control Policy declared prescription drug abuse a public health crisis in the US (ONDCP, 2011).

To facilitate a discussion of prevalence and to explore ways to mitigate this growing problem of Prescription Drug Abuse (PDA), a thorough understanding of the terms used to describe PDA is necessary. According to the Substance Abuse and Mental Health Services Administration (2007), nonmedical use of a psychotherapeutic drug is defined as “use of a prescription medication that was not prescribed for the user or taking a drug only for the experience or feeling it may cause.” Compton & Volkow (2006) defined prescription drug abuse as, “any intentional use of a medication with intoxicating properties outside of a physician’s
prescription for a bonafide medical condition, excluding accidental use.” By using the term “intoxicating properties” Compton & Volkow (2006) excluded classes of medications abused for reasons other than euphoria, such as prescription stimulants, which the Division of Population Surveys had included with its “experience or feeling” definition. These two definitions demonstrate the range of definitions for PDA in extant literature and the disagreements between them. Boyd & McCabe (2008) explain that defining abuse can be challenging because misuse of controlled prescription medications can happen by people who misuse someone else’s prescription and also by those who misuse their own prescriptions without a physician’s knowledge. Recognizing the problem of defining such diverse behavior, Smith et al. (2013) conducted a systematic review of definitions of all forms of “misuse, abuse and related events” and proposed their own definitions for each type of activity. They clarify that a misuse event signifies any intentional therapeutic use of a drug product in an inappropriate way; and an abuse event signifies any intentional, non-therapeutic use of a drug product, even once, for the purpose of achieving a desirable psychological or physiological effect. This definition of misuse is broad, it allows researchers to capture various forms of misuse, based on the type of medication being misused, the motives and techniques for misuse, and the methods of acquiring the medication. According to Boyd & McCabe (2008), there are four types of PDA possible depending on whether the prescription belong to the abuser or someone else, and whether the motivation for use was for the purpose of self-treatment or euphoria.

The focus of this study is on the abuse or misuse of psychostimulants commonly prescribed for diagnoses such as Attention Deficit Disorder (ADD) and Attention Deficit Hyperactivity Disorder (ADHD). Stimulant abuse can occur in multiple forms such as the abuse of Schedule II stimulants such as cocaine – which are mostly illegally manufactured, rather than
diverted from legal prescriptions – or the abuse of Schedule I stimulants such as ecstasy or 3, 4 – methylenedioxy – methamphetamine (MDMA) – which are not available legally. This study will focus on abuse of drugs which are available legally and are mostly acquired through prescription diversion. Any further mention of prescription stimulants in this document will refer to the drugs used to treat ADHD, unless specifically mentioned. The specific goals of this dissertation will be to help develop strategies to prevent abuse of prescription psychostimulants by identifying individuals who attempt to acquire prescriptions for the purpose of misuse, abuse or drug diversion. Over the course of chapters 2 to 4, this dissertation will attempt to identify individuals misusing prescription stimulants using a latent class analysis of known risk factors from administrative claims data, and by developing a subtle scale that can be administered in the physician’s office during the diagnosis of ADHD or ADD. A combination of both of these techniques, refined by thorough careful study, will help curb misuse or abuse of prescription stimulants. The rest of this chapter will deal with the impact of prescription drug abuse (with a special focus on stimulant abuse), the prevalence of stimulant abuse, intentions of stimulant abuse, a review of their impact on academic performance, and commonly available sources of stimulants for abuse.

Prevalence of PDA

It was estimated in 2013 that 54.3 million individuals reported overall lifetime prevalence of PDA, and 16.7 million individuals reported misusing or abusing prescription drugs in the past year. Of the 16.7 million individuals misusing prescription drugs, over 12.5 million were using opioids, 6 million were using tranquilizers and 3.3 million were using stimulants. The number of individuals misusing prescription drugs was greater than the number of illicit drug users.
combined (such as heroin, cocaine, ecstasy, and hallucinogens), and is second only to the prevalence of marijuana use (SAMHSA, 2013a). PDA cost the system $181 billion in 2002 (Manchikanti, 2006; ONDCP, 2004). The prevalence of PDA has increased by more than 250% in the last 2 decades. Between 1992 and 2003, there was an 94% increase in the number of adults abusing controlled substances (Bollinger et al., 2005). The impact of this increase can be seen in the change in frequency of hospitalizations and emergency room visits attributed to PDA. According to the Drug Abuse Warning Network (DAWN), between the years 2004 and 2008, medical emergencies due to PDA increased 81% and emergency room visits increased 97%. In 2008 alone, 54% of all drug related ER visits were caused by PDA (SAMHSA, 2011).

In recent years, a new group of individuals, i.e., young adults enrolled in colleges and schools, has emerged as a prominent abuse population. Between 1992 and 2003, there was a 212% increase in the number of 12 to 17 years olds abusing controlled substances, whereas the prevalence among adults grew by only 85% (Bollinger et al., 2005). About 13% of 18 to 25 year olds engage in PDA, compared to 7% in the 12 to 17 year age group (NIDA, 2013).

Prescription Stimulants

Stimulants are a class of psychoactive drugs that can improve cognition. They include illegal substances such as cocaine, and crystal meth; and legal prescription drugs such as Adderall (dextrompehtammine), Ritalin (methylphenidate), and Concerta (methylphenidate). They are commonly prescribed to treat symptoms of Attention Deficit Hyperactivity Disorder (ADHD). Stimulants are known to reduce hyperactivity, impulsivity, inattentiveness, socially aggressive behavior, and increase vigilance, reaction time, task persistence, productivity,
working memory, handwriting, fine motor speed, energy levels, alertness, self-esteem, coordination, elevated mood, reduced appetite, and extended wakefulness among those who truly have ADHD (Barkley et al., 2003; Zullig & Divin, 2012). After a thorough review of the effect of stimulants on various characteristics related to academic performance, Smith & Farah (2011) conclude that stimulants enhance declarative learning, working memory, cognitive control in some individuals and might possibly cause cognitive enhancement in some others, but these effects were too small to actually make a difference. However, most of these conclusions stem from studies involving students with ADHD, meaning these results cannot be extended to students without ADHD who might be misusing stimulants.

While the positive effects of stimulants on academic performance, in individuals with or without ADHD, lacks substantial evidence, stimulants are known to cause side-effects. The commonly mentioned side-effects include insomnia, headaches, irritability, nervousness, tics, significant weight loss, anxiety, anorexia, gastrointestinal distress, hallucinations (in the form of amphetamine psychosis), talkativeness, agitation, anger, paranoia, delusions, personality changes, mood swings, cardiovascular complications, and hypertension (Barkley et al., 2003; Hamilton, 2009; White, Becker-Blease & Grace-Bishop, 2006). Charach, Ickowicz & Schachar (2006) conducted a 5-year cohort study and found that while stimulants can improve symptoms of ADHD for up to 5 years in children, adverse effects tend to persist over the longer term. The FDA has also issued a blackbox warning for cardiovascular complications for prescription stimulants. The use of stimulants, even if taken legitimately, can result in increased Emergency Room (ER) visits (Miller et al., 2004). The number of stimulant-related ER visits have actually more than doubled between 2005 and 2010, and are responsible for approximately 40,000 ER visits per year (SAMHSA, 2013b).
While long-term data on effects of stimulant use is scarce, two effects have been studied by many researchers. The first is the effect of stimulant use on future substance abuse. Some studies have shown that use of stimulants is correlated with future substance abuse (Barkley et al., 2003). Other studies show that ADHD medication actually has a protective effect against future substance abuse (Biederman, 1999), while yet others have found no relationship between the two (Molina et al., 2013; Kaloyanides et al., 2007). The problem with most of these studies is that they cannot account for the bias of the abuse liability of the ADHD patient independent from the ADHD medication. In other words, they cannot assess how likely the subject would be to engage in substance abuse had he not received the ADHD prescription. Therefore, while available evidence raises some concerns about future effect of stimulant use, it is mostly inconclusive.

The second long-term effect of stimulants concerning younger patients is that of effect on growth rates. Several researchers have found that long-term use of stimulants can cause stunted growth rates among children (Toomey et al., 2003; Swanson et al., 2006; Charach et al., 2006; Swanson et al., 2007). In addition to the negative effect on growth rates, it was also found that children taking stimulants do not show rebound growth after drug use is discontinued (Swanson et al., 2007). The only study that did not find a significant effect of stimulant use on long-term growth rates was limited by a small sample size (Zachor et al., 2006). Despite these side-effects, White, Becker-Blease & Grace-Bishop (2006) report that about 79% of those taking stimulants report that they have no concern about stimulant abuse.

Abuse of stimulants can also cause depression (Teter et al., 2010) and addiction or drug dependence (White, Becker-Blease, & Grace-Bishop, 2006). Prescription stimulants used for treatment of ADHD are classified as a Schedule II controlled substance because they have a high abuse liability, and cause withdrawal effects such as depression, anxiety, and severe fatigue.
Manchikanti (2006) summarizes that prescription stimulants like methylphenidate have a lot in common with cocaine. They both bind to the similar sites in the brain and cause an increase in dopamine levels which leads to euphoria. While oral doses of stimulants might not cause a rush of dopamine equivalent to that of cocaine, it is reported that high doses of stimulants, taken by oral or intranasal routes, can cause high risk of addiction. Co-ingestion with other drugs can also increase abuse liability (White, Becker-Blease & Grace-Bishop, 2006; Volkow & Swanson, 2003). Smith & Farah (2011) found that 1 in 20 users of stimulants actually meet the criteria for being drug dependent. Whiteside et al. (2015) found that 21.8% of those taking stimulants had a strong desire to misuse on a weekly/daily basis and 8.6% had health, social, legal or financial problems which they would consider secondary to stimulant abuse.

Epidemiology of stimulant abuse

The National Institute on Drug Abuse identifies individuals between the ages of 18 and 25 years as a high risk group for abuse of prescription drugs (NIDA, 2013). While opioids, marijuana and stimulants are all commonly abused in the college population, research suggests that stimulants are the most frequently abused drugs (Babcock & Bryne, 2000). McCabe et al. (2014) provide evidence that the problem of stimulant abuse is actually of greater concern in the young adult age group than other drugs. In the decade from 2003 to 2013, the use of opioids decreased among college-aged individuals and use of stimulants and frequency of use of stimulants increased in the same time period. They also found that high frequency use (3 or more occasions) was normative among stimulants whereas low frequency use (1 or 2 occasions) was normative among sedatives and opioids.
The true prevalence of prescription stimulant abuse in college and university settings is difficult to measure. A 2012 systematic review concluded that most studies found less than 5% stimulant abuse in the 12 to 17 year old age group (Young, Glover & Havens, 2012). In the 18 to 25 year old age group, many studies report a prevalence of 4 to 8% (Frankenberger, 1990; Zullig & Divin, 2012; Poulin, 2001; Teter et al., 2005; Johnston et al., 2014; Whiteside et al., 2015; Novak et al., 2007); while others found a prevalence of 10% or higher in the same population (LeFever & Dawson, 1999; Rowland et al., 2002; Johnston et al., 2005; Marsh et al., 2000; McCabe & West, 2013; White et al. 2006; Babcock & Bryne, 2000; Hall et al., 2005; Bavarian et al., 2013). Two longitudinal studies were conducted in this population and both reported higher rates than any of these other studies. Garnier-Dysktra et al. (2012) found that by the end of four years in college, 61.8% of students were offered stimulants and over 31% of them accepted. As part of a 10-year longitudinal study, Wilens et al. (2006) found that only 56% of students who were taking prescription stimulants actually had ADHD.

Most of these estimates of prevalence of misuse or abuse of stimulants are obtained from direct online surveys where participants are asked to disclose any illicit use behavior. Because such use is considered unacceptable and, many times, these drugs are obtained illegally by prescription diversion, individuals may not be willing to disclose their behavior. Dietz et al. (2013) found that direct online surveys can only present an underestimate of true abuse prevalence. They administered a survey in Germany using an innovative technique that ensures respondent privacy, called Randomized Response Estimates, and found that the true prevalence of using stimulants and other cognitive-enhancing drugs is closer to 20%.

The recent reports of increased levels of stimulant abuse are supported by the fact that the number of prescriptions being written for stimulants has also grown steadily (Fortuna et al.,
The prevalence of ADHD, usually estimated at 3 to 7%, has also increased in the past few years (Visser et al., 2010). The CDC reports that legitimate use of stimulants for children under 18 has increased 5 times in the period from 1988-1994 to 2007–2010 (National Center for Health Statistics, 2014). And while 75% to 97% of actual ADHD patients respond positively to stimulant treatment (Barkley et al., 2003), ADHD may also be over-diagnosed (Kube, 2002). Angold et al. (2000) found that only 3.4% of their student sample actually had ADHD, but about 7.3% of them had prescriptions to treat ADHD. With a mean score of 3.54 on a scale of 1 to 5, a college student population surveyed by Hall et al. (2005) agrees that ADHD is over-diagnosed in the college population. Zgierska, Miller and Rabago (2012) explain that the rise in rate of prescriptions for stimulants might also be because patients are becoming more aware of stimulants and want to experiment with them, while physicians are under increased pressure to prescribe these medications to keep their patients satisfied.

The most common reason for misuse of stimulants is to improve academic performance or concentration. Manchikanti (2006) reports that 43% of students use stimulants to help with their school work, 31% use them to deal with other problems, and 22% use them to get high. Hamilton (2009) reports that the most common motives were concentration and alertness. In a longitudinal study across four years of college, Garnier-Dysktra et al. (2012) found that curiosity was the primary motive in early years, but academic performance becomes the primary motive later in college. Teter et al. (2005) also found concentration to be the most common motive for stimulant misuse. Interestingly, they found that the respondents who had reported using stimulants “only to study” also reported use of alcohol and other drugs, used to get high, as often as those who used stimulants “to get high”, suggesting that very few individuals might actually
be using stimulants solely for the purpose of academic improvement. Other motives for abuse or misuse as reported by Teter et al. (2005), in their systematic review, include use as a study-aid for all-nighters, euphoria, recreational tool in combination with alcohol, and as a reinforcement tool. The academic motives also explain why young adults enrolled in colleges were more likely to abuse stimulants than those not enrolled in educational institutions (Teter et al., 2005). Only 14% of stimulant abusers thought that stimulants lead to long-term academic achievements (Hall et al., 2005).

Hall et al. (2005) found that 27% of students took stimulants during finals week, 15.5% took them before tests, and 12% took them when they “partied”. A 2010 National Survey of Counselling Centers found that 91% of college counselling directors believe that many students are facing severe psychological problems on campus. The prevalence of mental health illnesses on campus is rising and the odds of abusing stimulants among students who reported feelings of hopelessness, sadness, depression, and suicide attempts were 1.2 to 1.4 times that of students who did not report these incidents (Zullig & Divin, 2012). In fact, Arria & Dupont (2010) recommend that stimulant abuse can be used as a marker for academic difficulties and mental health problems.

A study of the sources of drugs for abusers of stimulants found that 70% of abusers began use after starting college. Of the students abusing stimulants in college, 87.1% acquired drugs from friends who had prescriptions, 30.4% obtained them from acquaintances and 26.4% abused their own medications without the knowledge of their prescriber (Bavarian et al., 2013). Maxwell (2011) also found that obtaining drugs from a friend or relative was the most common way to acquire the drug (55%). They found that 18% of individuals abused their own prescription, 5% obtained drugs from a drug dealer or a stranger and 0.4% used the Internet to order their
medications. Other researchers have also found that obtaining drugs from a friend or a relative is by far the most common way for obtaining prescription drugs for the purpose of abuse (Lessenger & Feinberg, 2008; McCabe et al., 2014). More than half of college students thought it was easy or somewhat easy to acquire stimulants for illicit use and they obtained it at a cost of $1 to $5 per pill (White, Becker-Blease and Grace-Bishop, 2006; Hall et al., 2005). Medication diversion, or the practice of using prescription medications for purposes other than their intended use, such as for selling or giving away, is incredibly common with stimulants. Anywhere from 25% to 54% of individuals with abuse-liable prescriptions are approached for diversion of their medication (McHugh, Neilsen & Weiss, 2015; McCabe et al., 2014; McCabe et al., 2004, 2006; Poulin, 2001; Moline & Frankenberger, 2001). Wilens et al. (2006) found that 11% of individuals with legitimate ADHD prescriptions diverted their meds. Levine & Coupey (2009) found that 25% of students with a legitimate prescription gave away their medications.

In a longitudinal study of stimulant misuse behaviors, Garnier-Dykstra et al. (2012) found that rates of misuse of one’s own prescription increased in later years in college. They suggest that this effect was possible because “upper classmen might seek out a diagnosis of ADHD as a means of ensuring a steady supply of prescription stimulants.” When Angold et al. (2000) found that more individuals had been prescribed stimulants than those who actually had ADHD, they explained that it was due to over-diagnosis, while it might very well also be explained by individuals who were faking ADHD for the sake of a prescription. White, Becker-Blease and Grace-Bishop (2006) explain that in order to curb stimulant abuse, attention should be paid to “whether students might fake ADHD or ADD symptoms to obtain stimulants for planned misuse or abuse or for resale.”
Feigning or malingering of ADHD

Drug seeking behavior among stimulant abusers often manifests itself as students attempting to malinger attention deficit disorders in order to obtain legal prescriptions for stimulants. Hence, the ability of health practitioner to identify drug seeking behavior is crucial to decreasing drug abuse. However, in a study of opioid abuse, Weiner et al. (2013) found that physicians in the emergency room had a sensitivity of 63.2%, specificity of 72.7%, and positive predictive value of 41.2% for identifying drug seeking behavior. It is reported that only 19% of physicians were trained in school to identify drug diversion and only 40% of them were trained to identify PDA and addiction. In contrast, about 50% of pharmacists are trained to identify drug diversion or PDA and addiction. In addition, 43% of physicians do not ask about drug abuse when taking a patient’s history (Bollinger et al., 2005).

Several studies show that 10% to 50% of students evaluated for ADHD in a University setting might be exaggerating or feigning their symptoms (Suhr et al., 2008; Sullivan, May & Galbally, 2007; Jasinski & Ranseen, 2011; Harrison & Edwards, 2010; Pella et al., 2011). The promise of incentives such as access to stimulants, which can be misused or sold, and academic accommodations, provided to students diagnosed with learning disorder, and the decreasing stigma associated with rising awareness of the condition, has caused increasingly more students to feign or exaggerate their symptoms in order to be diagnosed with ADHD (Slick, Sherman & Iverson, 1999). There exists no standardized, statistically valid method for detection of malingering of ADHD (Harrison, Edwards & Parker, 2007), making it very easy to fake responses to appear ADHD-like on most ADHD diagnostic scales (Booksh et al., 2010; Harrison, & Edwards, 2010; Quinn, 2003). Jasinski & Ranseen (2011) compiled evidence to show that ADHD can be faked very easily during physician interviews, on self-report inventories, observer
symptom ratings, cognitive measures and even tests of memory, executive function and attention. Symptom Validity Tests (SVT) provide the best opportunity at identifying malingerers among existing methods. However, even they suffer from poor sensitivity (35% to 63%, depending on the test) and are time intensive, and expensive (Jasinski et al., 2011; Marshall et al., 2010; Jasinski & Ranseen, 2011).
RESEARCH OBJECTIVES

In order to better control the abuse of prescription stimulants among young adults enrolled in colleges, there exists a need to understand the stimulant use behavior, and to identify the individuals who attempt to feign symptoms of ADHD in order to gain access to the medication. The goal of this dissertation is to attempt to identify individuals misusing stimulants and prevent stimulant abuse by developing an innovative methodology to identify early abusers.

The specific aims of this dissertation are

1. To explore the feasibility of identification of prescription stimulant abuse using large databases (Paper 1).
2. To develop a subtle behavioral self-reported scale, the Subtle ADHD Malingering Screener (SAMS), for use in the primary care setting to identify malingering among individuals diagnosed with ADHD (Paper 2).
3. To test the ability of the newly developed scale, SAMS, to detect faking among adults diagnosed with ADHD and compare it to other existing scales (Paper 3).


CHAPTER 2: PAPER 1
IDENTIFICATION OF PATTERNS OF STIMULANT USE: AN ANALYSIS OF MEDICAID AND PRESCRIPTION MONITORING PROGRAM DATA FROM THE STATE OF MISSISSIPPI

*Formatted to the requirements of Drug and Alcohol Dependence*
Title: Identification of Patterns of Stimulant Use: An Analysis of Medicaid and Prescription Monitoring Program Data From the State of Mississippi

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Running title: (60 characters) Development of the Subtle ADHD Malingering Screener

Word count – Abstract: 243/250; Main text: 3,473/4,000
ABSTRACT

Background

An increase in prevalence of prescription stimulant abuse has led to concerns about stimulant-related addiction, emergency room visits, and other adverse effects. The aim of this study is to explore the feasibility of the identification of prescription stimulant abuse by categorizing stimulant users using Mississippi Medicaid administrative claims data and Mississippi Prescription Monitoring Program data.

Methods

This study employed a retrospective design to follow a cohort of prescription stimulant users using data from Mississippi Medicaid administrative claims and the Mississippi Prescription Monitoring Program, for the years 2014 and 2015. Risk factors for stimulant abuse were used to characterize latent classes among prescription stimulant users. Predicted latent class membership was used to predict chances of being diagnosed with dependent or nondependent stimulant abuse.

Results

A latent class model with 2 classes was selected as the best fit for this sample. The first latent class, comprising 4.1% of the sample, was characterized by a significantly higher proportion of cash prescriptions, new starts, and significantly lower prevalence of ADHD, and fewer unique
pharmacies visited. However, latent class membership was not significantly predictive of diagnosis of stimulant abuse (p = 0.802).

Conclusions

This study shows the value of commonly used risk factors in identification of prescription stimulant abuse. It also categorizes the various patterns of use of prescription stimulants and tests its ability to predict stimulant abuse diagnoses. Further research is needed to test the validity of these latent classes in the prediction of stimulant abuse.
INTRODUCTION

1.0 Introduction

Prescription stimulants such as amphetamine and methylphenidate are commonly prescribed to treat symptoms of Attention Deficit Hyperactivity Disorder (ADHD). These drugs are classified as schedule II controlled substances because they have a high abuse liability (Cohen, 2013). It is estimated that over 3.3 million individuals misused stimulants in 2013 alone (SAMHSA, 2013). Between 2006 and 2011, the nonmedical use of prescription stimulants among adults increased by 67%, and stimulant-related emergency room visits have more than doubled (Chen et al., 2016). Repeated use of prescription stimulants can also lead to drug dependence or addiction among individuals with and without ADHD (Bollinger et al., 2005; National Center for Health Statistics, 2014). The prevalence of drug dependence is estimated to be 1 in every 20 stimulant users, and is steadily increasing (Bollinger et al., 2005; National Center for Health Statistics, 2014; Smith & Farah, 2011). Abuse of stimulants can lead to a variety of side-effects such as insomnia, headaches, significant weight loss, anxiety, delusions, mood swings, cardiovascular complications, and hypertension (Barkley et al., 2003; Charach et al., 2006; Hamilton, 2009; Smith & Farah, 2011; White, Becker-Blease & Grace-Bishop, 2009).

An understanding of the patterns of use is essential to identification, treatment, and even prevention of stimulant misuse. Research about characteristics and patterns of drug use have been conducted in the area of alcohol abuse (Agrawal et al., 2006; Chiauzzi, DasMahapatra, & Black, 2013), and substance abuse (Carlson et al., 2005; Falck et al., 2005; Kelly et al., 2015;
Morasco & Dobscha, 2008; Patra et al., 2009; Sherman et al., 2009). For example, Sullivan et al. (2010) used data from Arkansas Medicaid and a commercial insurance plan to develop an opioid misuse score that correlates to possible indicators of misuse. Chiauzzi et al. (2013) classified college students into four different classes based on a combination of their alcohol and drug use frequencies. However, such research is lacking in the area of prescription stimulant abuse.

1.1 Characteristics of stimulant misuse

Stimulant use patterns can be challenging to characterize because of the varying frequencies of use among both legal and illegal users of stimulants. For example, individuals with legal stimulant prescriptions might take their medication every day or choose to use it infrequently, depending on their needs, and the severity of their symptoms (Caisley & Muller, 2012). Individuals misusing stimulants might also have varying patterns of use, depending on whether they are drug dependent, or if their motivation for misuse is for academic performance-related reasons (Garnier-Dysktra, et al., 2012; Moore et al., 2014). This varying frequency of use is also commonly seen among opioids; hence, several of the characteristics applicable to identification of opioid misuse can be used to help drive research in the identification of prescription stimulant misuse.

Risk factors commonly used to identify misuse of opioids include doctor shopping, high frequency of prescriptions, familial availability of prescriptions, and early refills (Katz et al., 2010; Morasco & Dobscha, 2008; Sansone & Sansone, 2012; Van den Bree et al., 1998). Several of these risk factors have been shown to be relevant in misuse of prescription stimulants. For example, Van den Bree et al. (1998) demonstrated the importance of familial substance abuse in identifying stimulant misuse. High doses of oral stimulants taken non-medically are known to cause drug dependence (NIDA, 2014). Doctor shopping has been demonstrated to be a
successful technique for acquiring prescription drugs for misuse or diversion, in cases of both opioids and stimulants (Sansone & Sansone, 2012; Worley, 2012).

1.2 Objectives

The objective of the current study is to explore the feasibility of identification of prescription stimulant misuse using, administrative claims data to identify and characterize latent classes of prescription stimulant users, and study the relationship between the membership in each latent class and the diagnosis of stimulant abuse.
METHODS

2.0 Materials & Methods

2.1 Study design

This study employed a retrospective data analysis to follow a cohort of prescription stimulant users using data from the Mississippi Medicaid administrative claims and the Mississippi Prescription Monitoring Program, for the years 2014 and 2015. Risk factors for stimulant misuse were identified from the data and used to characterize latent classes of prescription stimulant users. Predicted latent class membership was then used to predict a distal outcome, i.e., the likelihood of being diagnosed with dependent or nondependent stimulant abuse. Approval was obtained from the University of Mississippi’s Institutional Review Board before researchers had access to the data.

2.2 Data source

The Mississippi Medicaid administrative claims data contains all claims paid for by Mississippi Division of Medicaid for beneficiaries enrolled in its fee-for-service or managed care plans. It contains separate datasets for pharmacy claims, inpatient claims, outpatient claims, and a beneficiary master file – that contains demographic and eligibility information of enrollees. Claims for Medicaid beneficiaries paid for with cash are not captured in this dataset. The Mississippi Prescription Monitoring Program (PMP) data were used in this study to capture the cash prescriptions of Medicaid beneficiaries. The patient ID in the PMP data was linked to the
beneficiary ID in the Medicaid data, offering the researchers comprehensive prescription information, hospital or outpatient use data, and diagnosis information.

2.3 Timeline

The study used data from July 1\textsuperscript{st} 2014 to June 30\textsuperscript{th} 2015 to identify Mississippi Medicaid beneficiaries who were filling prescriptions for stimulants within the state of Mississippi. The first dispensing event for prescription stimulants during this period was labelled as the index prescription. The period ranging from January 1\textsuperscript{st} 2014 to June 30\textsuperscript{th} 2014 was used as a washout period to check for medication and diagnostic history. Individuals identified during the study period were followed up to December 31\textsuperscript{st} 2015 in order to ensure that every participant included in the study had at least 6 months of follow up from their index date.

2.4 Inclusion/exclusion

All Medicaid beneficiaries needed to be continuously enrolled during the study period (January 2014 to December 2015). Participants were eligible if they were over 18 years of age at the beginning of the study period, could not have dual eligibility in Medicare, and could not be enrolled in long term care. Participants were also required to have at least 3 refills for stimulants during the study period (July 1\textsuperscript{st} 2014 to December 31\textsuperscript{st} 2015).

2.5 Latent Class Indicators & Their Operationalization

Risk factors for drug misuse identified from literature were used as indicators for the latent class analysis. The risk factors included in this study were the number of refills for prescription stimulants during the study period, percentage of early refills, percentage of refills paid for with cash (i.e., not paid for by Medicaid), excess distance travelled to obtain stimulants, average number of stimulants per enrollee in a given zipcode, and the number of unique doctors
and pharmacies who have prescribed and dispensed stimulants, respectively. In addition to these variables, two categorical variables: whether or not the patient had a new start on stimulant therapy, and the presence of an ADHD diagnosis in the data were also included.

Total number of refills, number of early refills, and percentage of prescriptions paid for in cash indicate intentions of misuse or abuse. Early refills were operationalized as obtaining a refill 2 or more days before the end of the supply from the previous prescription. Prescriptions paid for with cash were identified using the payment type variable found in the PMP database. Excess distance travelled to obtain stimulants indicates the number of times the patient travelled further than necessary to a doctor appointment for his/her stimulant prescriptions. It was operationalized as the number of times the participant has travelled more than the average distance travelled by all the Medicaid enrollees in his/her zipcode to obtain a stimulant prescription. Geographic variations were accounted for using the average number of stimulant prescriptions per eligible Medicaid enrollee in the zipcode in which the participant resides. Zipcode information for each beneficiary was obtained from the beneficiary master file. The number of unique pharmacies and doctors visited by each patient is used as a measure of doctor shopping, and was calculated using each of the patient’s visits during the follow up period. New therapy on prescription stimulants were defined as those patients who have no fills for stimulants during the 6 month washout period before their index prescription. Diagnosis for ADHD was identified using ICD9 and ICD10 codes present in the outpatient and inpatient Medicaid claims records of participating beneficiaries.

2.6 Outcome Variables

Medicaid beneficiaries who were found to be receiving treatment for dependent or nondependent stimulant abuse were used as the group of interest in this study. These patients
were identified from the ICD9 and ICD10 diagnosis codes found in the inpatient and outpatient claims records. These diagnosis codes are the closest approximation to a gold standard for identification of prescription stimulant abuse available in administrative claims data. Other demographic variables such as age, race, and gender were used as control variables in the analysis.

2.7 Analysis

Data management and analysis were conducted using MPlus (Muthen & Muthen, 1998) and IBM SPSS (Chicago, IL). Latent Class Analysis (LCA), using MPlus, was used to identify subgroups of individuals that were similar to each other based on chosen indicator variables, i.e., the risk factors for misuse (Lazarsfeld & Henry, 1968). LCA was chosen because it uses model-based posterior probabilities to obtain subgroups, instead of a measure of distance in multidimensional space, such as that used in cluster analysis. It allows for latent classes with unequal variances and provides more interpretable results, while also being as reliable at prediction as discriminant analysis when using both categorical and continuous indicators (Carlson et al., 2005; Magidson & Vermunt, 2002). Similar approaches of identifying latent classes among drug abusers have been applied in the past to better understand patterns and behaviors of individuals dependent on other drugs (Agrawal et al., 2006; Carlson et al., 2005; Chiauzzi et al., 2013; Falck et al., 2005; Kelly et al., 2015; Morasco & Dobscha, 2008; Patra et al., 2009; Sherman et al., 2009).

Decisions about model fit were based on fit statistics such as the Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC), the Adjusted BIC (aBIC), and the entropy statistic. In general, lower values of AIC, BIC or ABIC and higher values of entropy indicate greater class separation and higher precision in class assignments. The Lo-Mendel-
Rubin Likelihood Ratio (LMR LR test) was used to choose the model with the appropriate number of latent classes (Carlson et al., 2005; Kelly et al., 2015). Most likely class membership for each observation was saved, and a logistic regression was performed, using SPSS, to identify the relationship between class membership (treated as an observed variable) and a combined endpoint of a diagnosis of dependent or nondependent stimulant abuse. Available demographic variables were used as covariates in the logistic regression. This regression was conducted in SPSS, instead of using the distal outcome option (DCATEGORICAL) in MPlus, because despite using true probabilities of class membership, the DCATEGORICAL feature does not provide an option to control for covariates (Asparouhov & Muthen, 2014). The use of most likely class membership as an observed variable is considered an acceptable approach when covariates are present in the analysis (Clark & Muthen, 2009). However, the DCATEGORICAL option in MPlus was also performed as a sensitivity analysis.
RESULTS

3.0 Results

3.1 Demographics

A total of 1022 Medicaid beneficiaries were eligible for the study. They were mostly female (70%), Caucasian (75%), and 31.7 years (SD: 10.99) old, on average. Most of the sample had a diagnosis of ADHD (83.6%), and 27.3% were identified as new starts on stimulant therapy. On average, 4% of the prescriptions were paid for in cash, and nearly 37% of refills were filled early. The average Medicaid beneficiary visited 2 unique pharmacies and 1.7 unique physicians for stimulant during the study period. Demographics of the study sample are provided in Table A1.

3.2 Latent classes

A latent class model with the 2 classes was chosen as the final solution in this study. The 3-class model had a significant LMR LR test, and lower values of AIC, and BIC, indicating satisfactory fit. However, the 3-class model provided a highly skewed class distribution with 95.2% in Class 1, 4.1% in Class 2, and 0.5% in Class 3. The 3-class model also suffered from a non-positive definite first-order derivative product matrix due to model nonidentification, resulting in a lack of replicability in the best loglikelihood value, despite increasing the number of random starts. In contrast, the 2-class solution, despite having slightly higher values of AIC (41970.03 vs 40226.28), and BIC (42098.19 vs 40403.74), showed a significant LMR LR test,
Table A1: Demographics of the sample, and distribution across latent classes

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Overall (N = 1022)</th>
<th>Class 1 (N = 42)</th>
<th>Class 2 (N = 980)</th>
</tr>
</thead>
<tbody>
<tr>
<td>n (%)/Mean[SD]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADHD*</td>
<td>854 (83.6)</td>
<td>28 (66.7)</td>
<td>826 (84.3)</td>
</tr>
<tr>
<td>New prescriptions*</td>
<td>279 (27.3)</td>
<td>19 (45.2)</td>
<td>260 (26.5)</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Caucasian</td>
<td>768 (75.1)</td>
<td>33 (78.6)</td>
<td>735 (75.0)</td>
</tr>
<tr>
<td>African American</td>
<td>139 (13.6)</td>
<td>8 (19.0)</td>
<td>131 (13.4)</td>
</tr>
<tr>
<td>Other</td>
<td>114 (11.2)</td>
<td>1 (2.4)</td>
<td>113 (11.5)</td>
</tr>
<tr>
<td>Female**</td>
<td>723 (70.7)</td>
<td>40 (95.2)</td>
<td>683 (69.7)</td>
</tr>
<tr>
<td>Dependent abuse of stimulants</td>
<td>28 (2.7)</td>
<td>0 (0)</td>
<td>28 (2.9)</td>
</tr>
<tr>
<td>Nondependent abuse of stimulants</td>
<td>32 (3.1)</td>
<td>3 (7.1)</td>
<td>29 (3.0)</td>
</tr>
<tr>
<td>Composite endpoint</td>
<td>54 (5.3)</td>
<td>3 (7.1)</td>
<td>51 (5.2)</td>
</tr>
<tr>
<td>Total number of prescriptions</td>
<td>11.8 [6.3]</td>
<td>11.1 [7.1]</td>
<td>11.8 [6.3]</td>
</tr>
<tr>
<td>Number of pharmacies**</td>
<td>2.0 [1.4]</td>
<td>0.7 [1.0]</td>
<td>2.03 [1.4]</td>
</tr>
<tr>
<td>Number of physicians</td>
<td>1.71 [1.0]</td>
<td>1.6 [1.1]</td>
<td>1.7 [1.0]</td>
</tr>
<tr>
<td>Percent of cash prescriptions**</td>
<td>4.4 [17.7]</td>
<td>84.6 [19.6]</td>
<td>0.9 [4.7]</td>
</tr>
<tr>
<td>Percent of early refills</td>
<td>36.9 [23.6]</td>
<td>41.4 [18.2]</td>
<td>36.7 [23.8]</td>
</tr>
<tr>
<td>Average stimulants per beneficiary in a zipcode</td>
<td>0.55 [1.4]</td>
<td>0.4 [0.3]</td>
<td>0.6 [1.4]</td>
</tr>
<tr>
<td>Age*</td>
<td>31.7 [11.0]</td>
<td>35.9 [10.5]</td>
<td>31.6 [11.0]</td>
</tr>
</tbody>
</table>

Note: * – p < 0.05; ** – p < 0.0001
and demonstrated satisfactory replicability in the best loglikelihood value. The 2-class model also had a high entropy value of 0.999. As stated by Carlson et al., (2005) “LCA classification should be driven by both statistics, and theory”, and classes must be “interpretable, and have a meaningful number of observations.” Therefore, for reasons of interpretability, model identification, and theoretical considerations, the 2-class model was chosen as the final solution (Geiser, 2013).

Of the 1022 subjects included in the latent class analysis, 4.1% (42) were included in the Class 1, and 95.9% (980) were included in Class 2. The distribution of each of the latent class indicators and the demographic variables across the two classes is provided in Table 1. Class 1, which includes only 42 individuals, was significantly older, with more females, less prevalence of ADHD, higher prevalence of cash prescriptions, and a fewer number of pharmacies visited. The prevalence of cash prescriptions in Class 1 was significantly higher than that in Class 2 (84.6% versus 0.9%). The percentage of early refills, though not statistically significantly, was also found to be higher in Class 1 than Class 2 (41.4% versus 36.7%). The smaller size of Class 1, along with the distribution of risk factors, suggest that Class 1 might be representative of stimulant misuse population. Individuals classified into Class 2 might be representative of regular/legal stimulant use behavior.

3.3 Prediction of stimulant abuse

The results of the 2-class solution indicate that Class 1 might be comprised of individuals likely to be misusing prescription stimulants. A logistic regression examining the effect of most likely class membership on dependent/nondependent prescription stimulant abuse, after controlling for demographic variables was not found to be significant (p = 0.802). The
demographic variable, race was dropped from the model because the distribution of race across the levels of the outcome variable were highly skewed leading to large standard errors.

Individuals in Class 1 had 1.17 times the odds of being diagnosed with prescription stimulant abuse, when compared with those in Class 2; however this increase in odds was not found to be significant (95% CI = 0.63 – 2.17; p = 0.802). When compared to males, females had 1.55 times the odds of being diagnosed with prescription stimulant abuse, but this difference was not statistically significant (95% CI = 0.07 – 2.24; p = 0.239). Subject age was found to be significantly related to the outcome with an odds ratio of 1.03 (95% CI = 1.01 – 1.04; p = 0.047; Table A2).

Table A2: Prediction of dependent/nondependent prescription stimulant abuse

<table>
<thead>
<tr>
<th>Variable</th>
<th>Odds ratio</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>1.2</td>
<td>0.63 – 2.17</td>
</tr>
<tr>
<td>Female</td>
<td>1.6</td>
<td>0.07 – 2.24</td>
</tr>
<tr>
<td>Age*</td>
<td>1.0</td>
<td>1.01 – 1.04</td>
</tr>
</tbody>
</table>

Note: Reference categories: Class 1 – Class 2; Female – Male.
Note: * – p < 0.05

In addition to the logistic regression conducted using SPSS and most likely class membership as the focal independent variable, the distal outcome analysis was also conducted using the DCATEGORICAL option in MPlus without any covariates (Asparouhov & Muthen, 2014). This approach takes into account measurement error and uncertainty of classification; the use of most likely class membership does not do so, which is an inherent limitation (Clark & Muthen, 2009). The DCATEGORICAL option has been suggested as the preferred method for analyzing categorical distal outcomes (Asparouhov & Muthen, 2014). This analysis revealed no
significant relationship between class membership and the combined endpoint (chi square = 0.226; p = 0.634), a finding consistent with the previous analysis.
4.0 Discussion

This study attempts to develop a deeper understanding of the differences in stimulant use behaviors between abusers and non-abusers, using a latent class analysis to first classify individuals according to their behaviors. It is one of the first studies to attempt to exclusively characterize stimulant use behaviors, and validate the developed latent classes using stimulant abuse diagnoses identified from administrative claims data. The use of administrative claims data to identify misusers of prescription stimulants revealed critical insights that can help future research in this area. This study was also the first to use a combination of Medicaid administrative claims data and PMP data to comprehensively capture all use of stimulants while estimating the risk behaviors.

A latent class model with 2 classes was selected as the best fit in this study. Over 95.9% of the sample was classified in Class 2, with only 4.1% classified into Class 1. This distribution, while skewed, was in line with the expectation of identifying a small proportion of misusers present in the population. Class 1 (N = 42) was expected to be related to abuse behavior because individuals classified in this class also had a lower proportion of ADHD diagnoses, and a significantly higher proportion of cash refills, an indicator expected to be correlated with abuse (Inciardi et al., 2009). In contrast, other indicators expected to be positively correlated with abuse, such as the number of unique pharmacies visited was significantly lower in this class (Sansone & Sansone, 2012; Worley, 2012). The other doctor shopping indicator variable,
number of unique physicians visited, was not significantly different between the two classes. Perhaps this difference in the distribution of risk factors contributed to the non-significant prediction of stimulant misuse.

The odds ratio from the validation procedures corresponding to latent class membership was not found to be statistically significant, indicating that behavioral risk factors of misuse were not predictive of stimulant misuse in administrative claims data. The practical significance of the latent classes needs to be judged within the context of the data used in this study. The diagnosis of dependent or nondependent stimulant abuse obtained from the medical records was the best available indicator for stimulant misuse. However, these diagnostic codes are used to identify abuse of both prescription stimulants and non-prescription illegal stimulants such as cocaine and heroin, leading to inaccurate capture of the outcome variable. There is also a possibility that stimulant abuse was underdiagnosed in the Medicaid population. Furthermore, individuals associated with risk behaviors such as cash refills, early refills, or doctor shopping might be diverting their prescriptions, and not misusing the medications themselves, and therefore will never be diagnosed with stimulant abuse. Finally, while the direction of relationship between stimulant abuse and latent class membership was in the right direction, perhaps the sample size of abusers was too small for a significant finding. It is possible that any combination of these reasons was responsible for the non-significant finding obtained in this study. The latent classes obtained in this study might still be indicative of stimulant misuse, but further research into the stimulant use behavior, perhaps using alternative validation techniques, is needed.

4.1 Limitations & Conclusions

While this study was one of the first to characterize latent classes of stimulant users, it carries limitations derived from the datasets used. Administrative claims data, even combined
with PMP data often do not provide a complete picture of the patient’s healthcare use. It is possible that stimulant abusers filled prescriptions outside of state limits or obtained the medications illegally, both of which are not captured by available data. Other latent class indicators, such as presence of an ADHD diagnosis, prescription history for identification of new prescriptions were limited by the fact that only 6 months of historical data were available. The datasets used in this study were merged based on an encrypted beneficiary identification number, and it is possible that some claims were wrongly attributed to other patients. Thorough quality checks were conducted on the PMP data prior to this study to ensure they were linked to the correct beneficiary identification number, and this error, if existing, is expected to be minimal.

The limitations of the outcome variable could have influenced the validation of the latent classes, and the prediction of stimulant abuse status. It is possible that many individuals classified in Class 1 were in fact abusing prescription stimulants, but had not been diagnosed; but there was no way to know their true misuse status from the data. Hence the findings of the prediction of stimulant misuse using latent classes need to be treated with caution and probably represent an underestimation. It is possible that alternative validation mechanisms with more reliable identification of misusers might have discovered a correlation with the latent classes obtained in this study.

This study demonstrates the value of latent class techniques to help identify variations in patterns of stimulant use, while also displaying the limitations of administrative claims databases in capturing true misuse status. Prescription stimulant misuse has increased in recent years (Chen et al., 2016), and techniques to identify this misuse need to be further researched to help address this problem.


Clark, S.L. & Muthen, B. (2009). Relating Latent Class Analysis Results to Variables not Included in the Analysis. Mplus Web Notes. Available at:


CHAPTER 3: PAPER 2

DEVELOPMENT OF THE SUBTLE ADHD MALINGERING SCREENER (SAMS) FOR
IDENTIFICATION OF INDIVIDUALS MALINGERING ATTENTION DEFICIT
HYPERACTIVITY DISORDER

Formatted to the requirements of the Archives of Clinical Neuropsychology
Title: Development of the Subtle ADHD Malingering Screener (SAMS) For Identification of Individuals Malingering Attention Deficit Hyperactivity Disorder

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Running title: (60 characters) Development Of the Subtle ADHD Malingering Screener

Supplement data: Supplement 1: Malingerer instruction set

Word count – Abstract: 210/250; Main text: 3,287
ABSTRACT

Objective Development of a behavioral, self-reported, subtle scale, called the Subtle ADHD Malingering Screener (SAMS), for use in the primary care setting to identify malingering among individuals reporting symptoms of ADHD.

Method This study employs a cross-sectional experimental design using a self-administered computer-based survey distributed to conveniently sampled groups of college students with and without ADHD. Respondents were classified into three groups: the ADHD group, comprised of individuals with ADHD; the Control group, comprised of individuals without ADHD, and the Maligner group, comprised of individuals without ADHD who were instructed to feign ADHD. Factor analysis and psychometric testing were conducted to develop a final scale that can distinguish the Maligner group from the other groups.

Results A ten-item, two-factor solution was obtained with satisfactory model fit, reliability, and construct validity. The psychological factor contained six items, and the academic factor contained four items. Means for individual items and the sum subscale scores were all significantly different among the three study groups.

Conclusion The SAMS presents an innovative approach to identify malingering of ADHD symptoms, reduce overdiagnosis of ADHD, and address abuse of prescription stimulants. It is short, easy to administer, and presents significant potential for direct use in the clinical setting.
INTRODUCTION

1. Introduction

The abuse of prescription stimulants, typically prescribed for ADHD, on college campuses has been increasing in the past few years (Bollinger et al., 2005; Chen et al., 2016). The Substance Abuse and Mental Health Services Administration identifies individuals between the ages of 18 and 25 years as a high risk group for abuse of prescription drugs (SAMHSA, 2010). College-aged students use more stimulants than their counterparts not enrolled in college (Johnston et al., 2011; Johnston et al., 2016). Garnier-Dysktra et al. (2012) estimate that the prevalence of prescription stimulant abuse in college populations can range up to 31%. Between 2006 and 2011, the nonmedical use of prescription stimulants among adults increased by 67%, and stimulant-related emergency room visits have more than doubled (Chen et al., 2016).

1.1 Malingering of Attention Deficit Hyperactivity Disorder (ADHD)

Most adults misusing prescription stimulants obtain the drugs from friends/family (Bavarian et al., 2013; Maxwell, 2011; Lessenger & Feinberg, 2008; McCabe et al., 2014). Students who misuse stimulants might also be interested in seeking out a diagnosis of ADHD (Zgierska, Miller and Ribago, 2012; Garnier Dysktra et al., 2012). Obtaining an ADHD diagnosis offers students means to acquire prescription stimulants legally and additional privileges such as extra time on tests, and isolated test environments, that most colleges and universities offer to accommodate students with learning disabilities (Young & Gross, 2011; Jasinski & Ranseen, 2011). These benefits create external incentives that encourage malingering...
behavior (Slick, Sherman & Iverson, 1999; Binder, 1992). Researchers estimate that 20% to 50% of college students might be exaggerating or malingering about their ADHD symptoms during an evaluation (Suhr et al., 2008; Sullivan, May & Galbally, 2007; Harrison, 2006).

1.2 Detection of Malingering

Malingering of ADHD symptoms in the physician’s office can be fairly easy (Quinn, 2003; Fisher & Watkins, 2008; Harp et al., 2011; Jachimowicz & Geiselman, 2004). This is because it is difficult to accurately diagnose ADHD, and because physicians are often not adequately equipped to identify cases of malingering (Harrison, 2006; Bollinger et al., 2005). Tools commonly used for diagnosing ADHD, such as self-report inventories, observer symptom ratings, cognitive measures and test of executive functions, can all be faked easily (Quinn, 2003; Fisher & Watkins, 2008; Harp et al., 2011; Jachimowicz & Geiselman, 2004). Symptom validity tests often perform better at detection of malingering, but they are usually very expensive, time consuming, and require an expert for administration and interpretation (Jasinksi & Ranseen, 2011).

In order to detect malingering of ADHD, there is a need for tools that are short, economical, sensitive, and easy to administer, score, and evaluate. Subtle scales can offer all of these features, but they have not received much attention in the context of ADHD (Burkhart, Gynther & Christian, 1978). Popular examples of subtle scales include the Minnesota Multiphasic Personality Inventory (MMPI; Hathaway & McKinley, 1940) and the Substance Abuse Subtle Screening Inventory (SASSI; Miller, 1985), which are used to detect malingering of any mental illness, and for alcohol and substance abuse, respectively. Subtle subscales present in the MMPI and the Personality Assessment Inventory (PAI) have been used to identify
malingering of ADHD, but these scales were not designed specifically for ADHD, and hence they show poor sensitivity (Harp et al., 2011; Young & Gross, 2011; Rios & Morley, 2013). There is a need to develop subtle scales, grounded in theory, and tailored to identify malingering, especially in the context of ADHD (Musso & Gouver, 2012).

1.3 Objective

This study aims to develop a behavioral self-reported Subtle ADHD Malingering Screener (SAMS), for use in the primary care setting to identify malingering among individuals reporting symptoms of ADHD. In order for this scale to hold the most value in the detection of malingering of ADHD and to prevent misuse of stimulants, it needs to meet certain criteria: The scale needs to be short, easy to administer, and score; it needs to be suitable for administration in the primary care setting, and should not need additional training for interpretation; it needs to be tailored toward patients reporting ADHD symptoms; and it should display good sensitivity to malingering.
METHODS

2. Methods

2.1 Study Design

This study employs a cross-sectional experimental design using a self-administered computer-based survey distributed to conveniently sampled groups of college-enrolled adults with and without ADHD. Approval was obtained from the University of Mississippi Institutional Review Board.

2.2 Item Development

Potential SAMS items were developed based on the Accuracy of Knowledge (AoK) framework, which says that malingerers can be identified by “the assessment of a person’s level of relevant knowledge of the target condition that the person is attempting to simulate.” (Lanyon, 1997). New items were generated through an extensive literature review, and a series of in-depth interviews conducted with students with and without ADHD recruited from the University of Mississippi. Items from preexisting subtle scales such as the PAI, the MMPI, the Connor Adult ADHD Rating Scale (CAARS), and the Clinical Assessment of Attention Deficit – Adult (CAT-A) which fit the AoK framework were also included in the initial item pool. Using a combination of new items and items borrowed from preexisting scales, a total of 125 items were generated in accordance with scale development guidelines developed by Jackson (1966), Buss (1959), Loevinger (1957), and Clark & Watson (1995). A 7-point response format from “Strongly
Disagree” to “Strongly Agree” was used in order to allow for variability in responses (Comrey, 1988). Qualitative pretests were conducted using cognitive interviews to help refine the item pool.

2.3 Experimental design

This study employed a between-subjects design with alternate instruction sets (in both the quantitative pretest and the main data collection task). Similar techniques have been commonly used to develop and test subtle scales in extant literature (Cofer, Chance & Judson, 1949; Lanyon, 1970; Myerholtz & Rosenberg, 1997; Myerholtz & Rosenberg, 1998; Lees-Haley, English & Glenn, 1991; Wooley et al, 2012). Respondents were first asked to self-report diagnosis of ADHD. To validate self-reported ADHD, respondents were also asked time since ADHD diagnosis, time spent during ADHD diagnostic visit, and the specialty of the diagnosing practitioner. Respondents were then assigned to one of three groups as part of the experimental design.

Respondents who self-reported ADHD were instructed to respond to the test item pool honestly; this was called the ADHD group. Respondents who self-reported not having ADHD were randomized to one of two groups where they were either instructed to fake ADHD on the test item pool (Malingering group) (Quinn, 2003; Supplement 1), or instructed to respond honestly (Control group). Participants in the Malingering group were not given information about symptoms of ADHD or other coaching to help them feign because research shows that knowledge of ADHD or coaching did not significantly improve success rate of ADHD feigning (Booksh et al., 2010; Rios & Morey, 2013; Tucha et al., 2009). Manipulation checks were
included to ensure that the instructions were followed. In addition to the item pool, the survey also measured the respondent’s demographics and several other variables such as insurance status, housing status, expected GPA, stimulant use behavior, and frequency of use of healthcare services.

2.4 Pretest

A quantitative pretest was conducted to narrow the item pool and to filter the questions that did not differentiate well between the study groups. A total of 278 students from the University of Mississippi were recruited using the SONA Systems website, a psychology department research platform. Participants were offered research credits as incentive for participation in the study. There were a total of 53 completed responses in the ADHD group, 111 completed responses in the Malingerer group and 112 completed responses in the Control group.

Using the Student’s t-test, 38 items were identified from the initial test pool that showed significant discrimination between the Malingerer group and the ADHD group. These items were entered into a Principal Components Analysis (PCA) to estimate the factor structure of the scale (Gerbing & Anderson, 1988; DeVellis, 2011). Only responses in the ADHD group and the Control group were used in the PCA, because literature suggests that malingering might cause distortions in the factor structure (Myerholtz & Rosenberg, 1997; Myerholtz & Rosenberg, 1998). Items with loadings less than or equal to 0.4 or items loading heavily on more than one factor were deleted (Hinkin, 1995). Using a combination of the latent root criterion (or the eigenvalue greater than 1 rule) (Nunnally, 1978), the scree plot (Cattell, 1966) and parallel analysis (Franklin et al., 1995; O’Connor, 2000), two factors were obtained: a 6-item psychological factor, and a 4-item academic factor, named because of the content of the items
that loaded highly on each factor. Both factors demonstrated satisfactory reliability with a Cronbach’s alpha of 0.895 and 0.870, respectively.

2.5 Participants and study recruitment

For the main data collection task, a sample of the undergraduate population at the University of Mississippi was used. Subject recruitment was conducted through a series of announcements conducted in classes held across campus, in order to obtain a representative sample. All participants were offered extra course credit as an incentive for participation. In order to prevent coercion, students who did not wish to participate in the study were offered an opportunity to earn the same extra credit through comparable alternative assignments. Additional incentives, in the form of a chance to win one of five $25 gift cards, were offered to individuals assigned to the Malingerer group in order to match real world incentives for malingering. Interested students set up appointments with the research team, and completed the survey in person on a computer assigned to them. The survey was designed using Qualtrics, and all data were collected anonymously.
ANALYSIS

3. Analysis

Analysis was conducted using IBM SPSS AMOS 22.0 (Chicago, Illinois) and MPlus 7.4 (Muthen & Muthen). Descriptive statistics were calculated and compared across the three study groups. A confirmatory factor analysis (CFA) was conducted, in MPlus, using the factor structure obtained from the PCA in the pretest. Because the items were measured on an ordinal scale with limited response options, CFA was conducted using robust weighted least squares estimation (i.e., the WLSMV estimator in MPlus). This approach is recommended in cases of categorical outcome variables which violate the assumption of normal distribution (Newsom, 2015; Rhemtulla, Brosseau-Liard, & Savalei, 2012). Similar to the pretest, only responses in the ADHD group and the Control group were used in the CFA, because literature suggests that Malingering might cause distortions in the factor structure (Myerholtz & Rosenberg, 1997; Myerholtz & Rosenberg, 1998).

The loading estimates, standardized residuals and modification indices were used to identify items that can be considered for deletion. Model fit was estimated using the Chi Square statistic, the Comparative Fit Index (CFI), and the Root Mean Square Error of Approximation (RMSEA; Hair et al., 2006). Convergent validity and discriminant validity were estimated using the Gerbing & Anderson (1988) approach. The Fornell & Larcker (1981) approach to convergent and discriminant validity using Average Variance Extracted (AVE) was not applicable in this case because the CFA model was run using WLSMV estimators. Reliability for each factor was
assessed through Cronbach’s alpha and composite reliability (Hair et al, 2006; Fornell & Larcker, 1981)
RESULTS

4. Results

4.1 Sample Characteristics

A total of 637 respondents completed the survey. The respondent sample had a mean age of 20.5 years, was comprised of 63.6% females, 74.1% Caucasians, and 46.9% freshmen. 16.6% (106) of the sample self-reported ADHD, and 12.7% (81) self-reported other mental illnesses. Approximately 35% of sample self-reported misusing prescription stimulants. Eight respondents self-reported attempting to feign ADHD in a physician’s office. These 8 responses were excluded from all subsequent analyses because they do not belong in any one of the three predefined study groups. The breakdown of each of the demographic characteristics across the three study groups, and the significance of the difference between the three groups is provided in Table B1.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>ADHD N = 102</th>
<th>Malingers N = 264</th>
<th>Controls N = 259</th>
<th>$\chi^2$</th>
<th>df</th>
<th>p</th>
</tr>
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<tr>
<td>Age (Mean [SD]; F)</td>
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<td>20.5 [1.68]</td>
<td>20.5</td>
<td>2.38</td>
<td>2.625</td>
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<td>Female</td>
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<td>173 (65.5)</td>
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<td>Ethnicity</td>
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<td>175 (67)</td>
<td>201 (75.8)</td>
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<td>36 (13.6)</td>
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<td>%</td>
<td>N</td>
<td>%</td>
<td>p-value</td>
<td></td>
</tr>
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</tr>
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<td>6 (2.3)</td>
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<td>1 (0.4)</td>
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<td>Greek membership</td>
<td>62 (60.2)</td>
<td>116 (44.6)</td>
<td>122 (46.0)</td>
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<td>119 (45.6)</td>
<td>135 (50.9)</td>
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<td>Sophomore</td>
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<td>57 (21.8)</td>
<td>62 (23.4)</td>
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<td>Junior</td>
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<td>60 (23.0)</td>
<td>41 (15.5)</td>
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<td>Senior (and above)</td>
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<td>25 (9.6)</td>
<td>27 (10.2)</td>
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<td></td>
</tr>
<tr>
<td>Residence</td>
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<td>21.0</td>
<td>10</td>
<td>0.021</td>
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<td>123 (47.1)</td>
<td>142 (53.6)</td>
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</tr>
<tr>
<td>Fraternity/Sorority house</td>
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<td>14 (5.4)</td>
<td>10 (3.8)</td>
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<td></td>
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<tr>
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<td>1 (0.4)</td>
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</tr>
<tr>
<td>Parent/Guardian home</td>
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<td>3 (1.1)</td>
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<td></td>
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<tr>
<td>Off-campus housing</td>
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<td>103 (39.5)</td>
<td>107 (40.4)</td>
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</tr>
<tr>
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<td>2 (0.8)</td>
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<tr>
<td>Expected GPA</td>
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<td>31.9</td>
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<tr>
<td>3.5 to 4</td>
<td>31 (30.1)</td>
<td>122 (46.9)</td>
<td>124 (47.0)</td>
<td></td>
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<td></td>
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<tr>
<td>3 to 3.49</td>
<td>37 (35.9)</td>
<td>107 (41.2)</td>
<td>103 (39)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>2.5 to 2.99</td>
<td>27 (26.2)</td>
<td>28 (10.8)</td>
<td>30 (11.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 to 2.49</td>
<td>8 (7.8)</td>
<td>3 (1.2)</td>
<td>7 (2.7)</td>
<td></td>
<td></td>
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<tr>
<td>Below 2</td>
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<td>0 (0)</td>
<td>0 (0)</td>
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<td>Insurance status</td>
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<td>7.15</td>
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<td>0.848</td>
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<tr>
<td>Private health insurance</td>
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<td>181 (69.6)</td>
<td>194 (73.2)</td>
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</tr>
<tr>
<td>from parents/family</td>
<td></td>
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</tr>
<tr>
<td>Independent private health</td>
<td>7 (6.8)</td>
<td>14 (5.4)</td>
<td>15 (5.7)</td>
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<tr>
<td>insurance plan</td>
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<tr>
<td>Private health insurance</td>
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<td>14 (5.3)</td>
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<td></td>
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</tr>
<tr>
<td>from Employer</td>
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<td></td>
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</tr>
<tr>
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<td>14 (5.4)</td>
<td>13 (4.9)</td>
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<td></td>
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<tr>
<td>State Medicaid plan</td>
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<td>11 (4.2)</td>
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<td>Self-reported ADHD</td>
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<td>0 (0)</td>
<td>629.</td>
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<td>Other mental illnesses</td>
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<td>27 (10.2)</td>
<td>33.2</td>
<td>2</td>
<td>&lt;0.00</td>
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<tr>
<td>Time since ADHD Diagnosis</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Time period</td>
<td>Count</td>
<td>Percentage</td>
<td>Confidence Interval</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>-------</td>
<td>------------</td>
<td>---------------------</td>
<td></td>
<td></td>
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<tr>
<td>Less than 1 year ago</td>
<td>14</td>
<td>13.9%</td>
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<td></td>
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<tr>
<td>1 to 2 years ago</td>
<td>13</td>
<td>12.9%</td>
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<tr>
<td>3 to 5 years ago</td>
<td>27</td>
<td>26.7%</td>
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<tr>
<td>More than 5 years ago</td>
<td>47</td>
<td>46.5%</td>
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<table>
<thead>
<tr>
<th>Type of physician who diagnosed ADHD</th>
<th>Count</th>
<th>Percentage</th>
<th>Confidence Interval</th>
</tr>
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<tbody>
<tr>
<td>Primary Care Provider</td>
<td>11</td>
<td>10.8%</td>
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<tr>
<td>Specialist</td>
<td>83</td>
<td>81.4%</td>
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<tr>
<td>Not sure</td>
<td>8</td>
<td>7.8%</td>
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<table>
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<tr>
<th>ADHD Diagnosis visit time</th>
<th>Count</th>
<th>Percentage</th>
<th>Confidence Interval</th>
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<tr>
<td>Less than 30 minutes</td>
<td>20</td>
<td>19.4%</td>
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<tr>
<td>30 to 60 minutes</td>
<td>36</td>
<td>35.0%</td>
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<tr>
<td>60 to 120 minutes</td>
<td>29</td>
<td>28.2%</td>
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<tr>
<td>Greater than 120 minutes</td>
<td>10</td>
<td>9.7%</td>
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<th>Emergency room visits in the past 6 months</th>
<th>Count</th>
<th>Percentage</th>
<th>Confidence Interval</th>
</tr>
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<tbody>
<tr>
<td>Never</td>
<td>67</td>
<td>66.3%</td>
<td>150 (57.7) 171 (65.3)</td>
</tr>
<tr>
<td>1 to 3 times</td>
<td>29</td>
<td>28.7%</td>
<td>106 (40.8) 86 (32.8)</td>
</tr>
<tr>
<td>4 to 6 times</td>
<td>4</td>
<td>4.0%</td>
<td>4 (1.5) 5 (1.9)</td>
</tr>
<tr>
<td>More than 6 times</td>
<td>1</td>
<td>1.0%</td>
<td>0 (0) 0 (0)</td>
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<table>
<thead>
<tr>
<th>Hospital Visits in the past 6 months</th>
<th>Count</th>
<th>Percentage</th>
<th>Confidence Interval</th>
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</thead>
<tbody>
<tr>
<td>Never</td>
<td>100</td>
<td>98%</td>
<td>254 (98.1) 253 (96.2)</td>
</tr>
<tr>
<td>1 to 3 times</td>
<td>2</td>
<td>2.0%</td>
<td>5 (1.9) 10 (3.8)</td>
</tr>
<tr>
<td>4 to 6 times</td>
<td>0</td>
<td>0.0%</td>
<td>0 (0) 0 (0)</td>
</tr>
<tr>
<td>More than 6 times</td>
<td>0</td>
<td>0.0%</td>
<td>0 (0) 0 (0)</td>
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<th>Count</th>
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<th>Confidence Interval</th>
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<td>10</td>
<td>9.8%</td>
<td>49 (18.9) 55 (20.8)</td>
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<tr>
<td>1 to 3 times</td>
<td>63</td>
<td>61.8%</td>
<td>182 (70.3) 173 (65.5)</td>
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<td>4 to 6 times</td>
<td>23</td>
<td>22.5%</td>
<td>24 (9.3) 31 (11.7)</td>
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<tr>
<td>More than 6 times</td>
<td>6</td>
<td>5.9%</td>
<td>4 (1.5) 5 (1.9)</td>
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<table>
<thead>
<tr>
<th>Use of stimulants with a valid Rx</th>
<th>Count</th>
<th>Percentage</th>
<th>Confidence Interval</th>
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<tbody>
<tr>
<td>Never</td>
<td>96</td>
<td>94.1%</td>
<td>9 (3.5) 4 (1.5)</td>
</tr>
<tr>
<td>1 to 3 times</td>
<td>41</td>
<td>40.2%</td>
<td>81 (31.2) 97 (36.6)</td>
</tr>
<tr>
<td>3 to 5 occasions</td>
<td>12</td>
<td>30.0%</td>
<td>19 (23.5) 20 (21.1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Use of stimulants without a valid Rx</th>
<th>Count</th>
<th>Percentage</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Never</td>
<td>41</td>
<td>40.2%</td>
<td>81 (31.2) 97 (36.6)</td>
</tr>
<tr>
<td>1 to 2 occasions</td>
<td>11</td>
<td>27.5%</td>
<td>30 (37.0) 37 (38.9)</td>
</tr>
<tr>
<td>3 to 5 occasions</td>
<td>12</td>
<td>30.0%</td>
<td>19 (23.5) 20 (21.1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Frequency of stimulants misuse</th>
<th>Count</th>
<th>Percentage</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 to 2 occasions</td>
<td>11</td>
<td>27.5%</td>
<td>30 (37.0) 37 (38.9)</td>
</tr>
<tr>
<td>3 to 5 occasions</td>
<td>12</td>
<td>30.0%</td>
<td>19 (23.5) 20 (21.1)</td>
</tr>
<tr>
<td>History of illegal use</td>
<td>ADHD (42.5)</td>
<td>None (39.5)</td>
<td>Malingerer (40.0)</td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>-------------</td>
<td>-------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>Less than 1 year ago</td>
<td>8 (20.0)</td>
<td>40 (49.4)</td>
<td>40 (42.1)</td>
</tr>
<tr>
<td>1 to 2 years ago</td>
<td>15 (37.5)</td>
<td>27 (33.3)</td>
<td>42 (44.2)</td>
</tr>
<tr>
<td>3 to 5 years ago</td>
<td>8 (20.0)</td>
<td>11 (13.6)</td>
<td>11 (11.6)</td>
</tr>
<tr>
<td>More than 5 years ago</td>
<td>9 (22.5)</td>
<td>3 (3.7)</td>
<td>2 (2.1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Reasons for illegal use</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Experimental</td>
<td>7 (17.5)</td>
<td>21 (25.9)</td>
<td>22 (23.2)</td>
</tr>
<tr>
<td>Academic</td>
<td>33 (82.5)</td>
<td>72 (88.9)</td>
<td>84 (88.4)</td>
</tr>
<tr>
<td>Entertainment</td>
<td>2 (0.05)</td>
<td>14 (17.3)</td>
<td>12 (12.6)</td>
</tr>
<tr>
<td>Other</td>
<td>7 (17.5)</td>
<td>4 (4.9)</td>
<td>7 (7.4)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source of stimulants</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Borrowed from family/friends</td>
<td>27 (67.5)</td>
<td>67 (82.7)</td>
<td>76 (0.8)</td>
</tr>
<tr>
<td>Purchased from stranger/friend</td>
<td>10 (25.0)</td>
<td>27 (33.3)</td>
<td>32 (33.7)</td>
</tr>
<tr>
<td>Pharmacy</td>
<td>9 (22.5)</td>
<td>1 (1.2)</td>
<td>1 (1.1)</td>
</tr>
<tr>
<td>Other</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

ADHD: Attention Deficit Hyperactivity Disorder; SD: Standard Deviation; df: degrees of freedom; GPA: Grade Point Average

4.2 Manipulation Checks

The goal of the manipulation check was to ensure that the Malingerer group was following instructions to feign ADHD correctly. Items included in the manipulation check were those that were considered to be easy to feign; so the responses of the Malingerer group should resemble those of the ADHD group very closely. Table B2 shows the means, standard deviations, and p values of the differences between each of the three groups. Overall, it was found that the Malingerer group was not significantly different from the ADHD group on all but one of the items in the manipulation check, indicating that the instructions were clearly communicated and followed.
Table B2: Differences between the three groups among the items used in the Manipulation check

<table>
<thead>
<tr>
<th>Item</th>
<th>ADHD Mean (SD)</th>
<th>Malingerer Mean (SD)</th>
<th>Control Mean (SD)</th>
<th>ADHD vs Malingerer p</th>
<th>ADHD vs Control p</th>
<th>Malingerer vs Control p</th>
</tr>
</thead>
<tbody>
<tr>
<td>I have ADD/ADHD</td>
<td>6.5 (0.9)</td>
<td>5.2 (1.5)</td>
<td>1.5 (1.1)</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>I have difficulty keeping my focus while reading</td>
<td>6.2 (0.9)</td>
<td>5.9 (1.1)</td>
<td>3.8 (1.8)</td>
<td>0.10</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>I have trouble sitting still</td>
<td>5.8 (1.5)</td>
<td>5.6 (1.3)</td>
<td>3.3 (1.8)</td>
<td>0.61</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>I tend to act impulsively</td>
<td>5.2 (1.8)</td>
<td>5.1 (1.3)</td>
<td>2.9 (1.7)</td>
<td>0.63</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>I have trouble paying attention in class</td>
<td>6.1 (0.9)</td>
<td>6.0 (1.0)</td>
<td>3.5 (1.8)</td>
<td>0.65</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>

Note: Each item was scored on a scale of 1 through 7.

4.3 SAMS Items

A total of 10 items were identified from the pretest using a combination of individual item discriminatory power and the principal components analysis (PCA). Model structure obtained from the PCA contained 2 factors, the psychological factor and the academic factor, with 6 items and 4 items, respectively. Confirmatory Factor Analysis (CFA) using the WLSMV estimator was conducted using the model structured obtained from the PCA. In this measurement model, each item was allowed to load on only one of the two factors; non-target loadings were fixed to zero. The chi square statistic for the model fit was found to be 108.153 (df = 34; p < 0.0005), with a Root Mean Square Error of Approximation of 0.078 (90% CI=0.062-0.094), Weighted Root Mean Square Residual value of 0.752 and a comparative fit index of 0.986, indicating satisfactory model fit (Hair et al., 2006). Table B3 shows the mean sum subscale score for the psychological factor and the academic factor in each of the study groups. Both factors significantly differentiated all three study groups in post-hoc comparisons. The Malingerer group
scored significantly higher than the two other groups on both factors, indicating the ability of the SAMS to identify malingering behavior.

Table B3: Mean sum scale scores on each factor of the Subtle ADHD Malingering Screener (SAMS) in each study group

<table>
<thead>
<tr>
<th>Group</th>
<th>Psychological factor</th>
<th>Academic factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>ADHD group</td>
<td>19.7 (7.0)</td>
<td>10.6 (5.6)</td>
</tr>
<tr>
<td>Maligner group</td>
<td>26.4 (7.1)</td>
<td>15.8 (5.7)</td>
</tr>
<tr>
<td>Control group</td>
<td>11.0 (5.8)</td>
<td>5.5 (3.0)</td>
</tr>
<tr>
<td>Total</td>
<td>18.9 (9.6)</td>
<td>10.7 (6.7)</td>
</tr>
</tbody>
</table>

Note: Both the psychological factor and the academic factor significantly differentiated all three study groups in post-hoc comparisons (p < 0.05).

Note: The minimum and maximum possible score for each subscale are: Psychological factor = 6 – 42; Academic factor = 4 – 28.

4.4 Psychometric properties

Cronbach’s alpha for the psychological subscale was found to be 0.909, and that for the academic subscale was found to be 0.916, indicating satisfactory reliability scores. Convergent validity was demonstrated by the consistently high factor loadings for each item in the scale, as seen in Table B4. The correlation between the two subscales was found to be 0.793. The MODEL TEST option in MPlus was used to test if the correlation between the two latent variables was different from 1. With a p-value less than 0.0005, the correlation was shown to be significantly different from 1 indicating significant discriminant validity.
Table B4: Means, standard deviations, and effect sizes for each of the three study groups on each item in the Subtle ADHD Malingering Scale (SAMS)

<table>
<thead>
<tr>
<th>Item</th>
<th>Subscale</th>
<th>Standardized loadings</th>
<th>ADHD Mean (SD)</th>
<th>Malinger-Mean (SD)</th>
<th>Control Mean (SD)</th>
<th>ADHD vs Malinger d</th>
<th>ADHD vs Control d</th>
<th>Malinger vs Control d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item 1</td>
<td>PSYCH</td>
<td>0.772</td>
<td>3.9 (1.9)</td>
<td>5.2 (1.4)</td>
<td>2.1 (1.6)</td>
<td>-0.81</td>
<td>1.11</td>
<td>4.53</td>
</tr>
<tr>
<td>Item 2</td>
<td>PSYCH</td>
<td>0.652</td>
<td>4.2 (1.9)</td>
<td>5.1 (1.6)</td>
<td>2.6 (1.9)</td>
<td>-0.51</td>
<td>0.83</td>
<td>4.39</td>
</tr>
<tr>
<td>Item 3</td>
<td>PSYCH</td>
<td>0.842</td>
<td>3.0 (1.7)</td>
<td>4.4 (1.7)</td>
<td>1.6 (1.1)</td>
<td>-0.84</td>
<td>1.14</td>
<td>3.37</td>
</tr>
<tr>
<td>Item 4</td>
<td>PSYCH</td>
<td>0.721</td>
<td>2.2 (1.6)</td>
<td>3.4 (1.7)</td>
<td>1.5 (1.2)</td>
<td>-0.67</td>
<td>0.53</td>
<td>2.57</td>
</tr>
<tr>
<td>Item 5</td>
<td>PSYCH</td>
<td>0.759</td>
<td>2.8 (1.6)</td>
<td>4.1 (1.6)</td>
<td>1.6 (1.1)</td>
<td>-0.83</td>
<td>0.90</td>
<td>3.28</td>
</tr>
<tr>
<td>Item 6</td>
<td>PSYCH</td>
<td>0.875</td>
<td>3.5 (1.6)</td>
<td>4.3 (1.6)</td>
<td>1.7 (1.3)</td>
<td>-0.44</td>
<td>1.33</td>
<td>3.59</td>
</tr>
<tr>
<td>Item 7</td>
<td>ACAD</td>
<td>0.763</td>
<td>2.8 (2.1)</td>
<td>4.2 (1.7)</td>
<td>1.5 (1.0)</td>
<td>-0.73</td>
<td>0.97</td>
<td>3.18</td>
</tr>
<tr>
<td>Item 8</td>
<td>ACAD</td>
<td>0.899</td>
<td>2.5 (1.6)</td>
<td>3.8 (1.7)</td>
<td>1.3 (0.8)</td>
<td>-0.75</td>
<td>1.08</td>
<td>2.83</td>
</tr>
<tr>
<td>Item 9</td>
<td>ACAD</td>
<td>0.883</td>
<td>2.8 (1.8)</td>
<td>4.1 (1.7)</td>
<td>1.3 (0.9)</td>
<td>-0.79</td>
<td>1.15</td>
<td>3.10</td>
</tr>
<tr>
<td>Item 10</td>
<td>ACAD</td>
<td>0.925</td>
<td>2.5 (1.6)</td>
<td>3.8 (1.7)</td>
<td>1.4 (0.9)</td>
<td>-0.76</td>
<td>0.95</td>
<td>2.88</td>
</tr>
</tbody>
</table>

**Note:** All items significantly differentiated all three groups in post-hoc analyses; Factor scores are the standardized factor estimates obtained from the Confirmatory Factor Analysis. ‘d’ indicates effect size.

**Note:** Items have been blinded to protect the distribution of the scale. Please contact the authors for the full scale.
5. Discussion

This study is the first of its kind to develop a scale tailored toward identification of malingering in ADHD. As such, it offers great potential for direct use in the clinical setting. A ten-item, two-factor solution was obtained for the SAMS in this study. The CFA showed satisfactory model fit. With an RMSEA of 0.078 and a CFI value of 0.986, the SAMS scale meets the Hair et al. (2006) criteria of an RMSEA value less than 0.1 and a CFI greater than 0.9 necessary for a satisfactory model fit (Hair et al., 2006). Each of the ten items in the final factor solution showed high factor loadings (>0.6), and significant differentiation among the three study groups. The scale showed satisfactory reliability (Cronbach’s alpha > 0.9), and construct validity (AVE > 0.5) validity (Hair et al., 2006). Each individual SAMS item was also found to significantly differentiate all three groups in the study, and not just the ADHD group and the Malingering group.

The sum scale score was used to calculate the total score for the SAMS in order to preserve ease of scoring, and reduce time of administration in the physician’s office. The mean scores on both the psychological and academic factor follow patterns predicted by Lanyon (1997) in the Accuracy of Knowledge framework. The Malingering group consistently endorsed items more than the ADHD group or the Control group, and this response behavior can help identify the Malingering group.
The respondent sample obtained in this study is fairly representative of the demographics of the University of Mississippi’s student population (University of Mississippi Office of Institutional Research, Effectiveness, and Planning, 2016). Several of the demographic characteristics were found to be significantly different among the three study groups. While some of these, such as a higher incidence of comorbid mental illnesses in the ADHD group versus other groups, were expected, some others, such as higher Greek membership in the ADHD group, were unexpected. More than 35 of the sample self-report misuse of stimulants which was in line with findings from Garnier-Dykstra et al. (2012). Over 80% of the individuals in the ADHD group were diagnosed by a specialist, and more than 80% also spent greater than 30 minutes during their ADHD diagnosis visit. About 46% of the ADHD group were also diagnosed over 5 years ago. These findings support the validity of the self-reported ADHD measure against the presence of possible malingerers within the ADHD group.

The success of the experimental design was crucial to the development of the SAMS. The five items used in the manipulation check clearly indicate that the instructions used in the Malingerer group were simple, clear, and easy to follow. However, the Malingerer group and the ADHD group significantly differed (p < 0.01; Table 3) on one manipulation check item: “I have ADD/ADHD.” This finding was not unexpected, because the instructions provided to the malingerers asked them to imagine visiting the physician in order to obtain an ADHD diagnosis, implying that they had not been diagnosed yet (See supplement-1 for the Malingerer instruction set).
5.1 Limitations

This scale was developed using an experimental design, rather than a real-world malingerer population. This design was chosen to facilitate ease of identification of the malingerers and to help provide the required sample size in the Malingerer group. Despite the use of additional incentives, the Malingerer group in the study may not have been representative of the true malingerer population in the real world. The experimental design also prioritizes internal validity over external validity, which makes it difficult to generalize the psychometrics of the SAMS, calculated from one University population, to the real world setting. Finally, the ability of the SAMS to detect malingering of ADHD reduces potential access points for abusers, but does not directly reduce the problem of prescription stimulant abuse. Further testing and interventions need to be developed in order to achieve that goal.

5.2 Clinical Implications and Future Research

The SAMS presents an innovative approach to identify malingering of ADHD symptoms, reduce overdiagnosis of ADHD, and for early identification of prescription stimulant abuse directly in the clinical setting. It is designed to be short, inexpensive, and does not need additional training for administration, scoring or evaluation. These features make it a valuable resource for primary care providers. While further research is needed to develop a cutoff score, and calculate the sensitivity and specificity of the SAMS, this study shows the potential this scale holds for future clinical use. Future research in this area needs to test the ability of SAMS to resist faking in the real world and compare it with existing subtle scales that may be used for similar purposes. There is also a need to focus on the needs of malingerers identified by this scale, and to develop interventions that can help malingerers cope with their stressors and
address potential addiction problems. Finally, this study successfully demonstrates the methodology of developing a subtle scale with the application of a theoretical framework for item development. This technique can be applied in several other areas in healthcare such as the early identification of opioid abusers, injection drug users, and others to implement early targeted interventions.


APPENDIX – A: Malingering Group Instructions

“Imagine yourself having trouble in school. Things aren’t working out as you planned but your counselor’s only advice is to buckle down. You want to get some help. You hear about adult ADHD on a television show. When talking to a friend about it, your friend tells you that you could get special accommodations from the university, like untimed tests and rescheduling of exams if two are given on the same day. Your friend adds that the stimulant medications that are generally prescribed have minimal side effects and that you can take the medicine only when you need it, just for school. You decide to read a book on ADHD. You find out that some ADHD adults even collect social security benefits. You conclude that you have enough of the symptoms. You convince yourself that you have ADHD. You go to the doctor and you really want to get help. In order to get these benefits, you need to convincingly act like a person who has ADHD.”

CHAPTER 4: PAPER 3

PSYCHOMETRIC VALIDATION OF THE SUBTLE ADHD MALINGERING SCALE (SAMS) AND COMPARISON OF DIAGNOSTIC ACCURACY WITH THE PERSONALITY ASSESSMENT INVENTORY (PAI)

*Formatted to the requirements of the Archives of Clinical Neuropsychology*
Title: Psychometric Validation of the Subtle ADHD Malingering Scale (SAMS) and Comparison of Diagnostic Accuracy with the Personality Assessment Inventory (PAI)

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Running title: (60 characters) Psychometric Validation Of Subtle ADHD Malingering Screener

Supplement data: None

Word count: 2934 (Abstract: 241)
ABSTRACT

**Objective** Development of a cut-off score and psychometric testing of the Subtle ADHD Malingering Screener (SAMS), and comparison of its diagnostic accuracy with the Personality Inventory Assessment – Adult (PAI).

**Method** This study employs a cross-sectional experimental design using a self-administered computer-based survey distributed to conveniently sampled groups of college students with and without ADHD. Respondents were classified into three experimental groups: an ADHD group, a Control group, and a Malingering group, comprised of individuals who were instructed to feign ADHD. ROC curve analysis and CART analysis were used to determine a cutoff score. Diagnostic accuracy of the SAMS was compared to the Personality Assessment Inventory – Adult.

**Results** Using a combination of ROC curve analysis and CART analysis, respondents were classified as malingerers if their SAMS psychological factor score was greater than 15, and the SAMS academic factor score was greater than 7. The sensitivity of the SAMS for detecting malingering was found to be 90.4%, with a specificity of 80.1%. The SAMS showed superior performance compared to the PAI, as it had significantly higher sensitivity (90% vs 51%; p < 0.0005).

**Conclusion** This is the first study to estimate the diagnostic accuracy of the SAMS. The SAMS is recommended for use in the primary care setting setting to identify patients who need additional testing to confirm an ADHD diagnosis. Further research is needed to test the
generalizability of these findings. The SAMS can help reduce overdiagnosis of ADHD and potential misuse of stimulants by helping to identify malingering of ADHD symptoms.
INTRODUCTION

1. Introduction

Exaggeration of symptoms of Attention Deficit Hyperactivity Disorder (ADHD) or malingering of ADHD in the physician’s office is prevalent in 20 to 50% of college students (Suhr et al., 2008; Sullivan, May & Galbally, 2007; Harrison, 2006) and is on the rise due to the increasing abuse of prescription stimulants and the presence of external incentives to encourage malingering (Chen et al., 2016; Slick, Sherman & Iverson, 1999; Binder, 1992). Most attempts to mangle ADHD are successful because research suggests that faking of ADHD symptoms is fairly easy (Quinn, 2003; Fisher & Watkins, 2008; Harp et al., 2011; Jachimowicz & Geiselman, 2004).

1.1 Challenges in Detection of ADHD Malingering

Tools commonly used for confirming a diagnosis of ADHD include several scales such as self-report inventories, observer symptom ratings, cognitive measures, test of executive functions, and symptom validity tests (SVTs). Several researchers have shown that most of these tools have poor sensitivity toward malingering. Self-report inventories such as the ADHD Behavior Checklist have been shown to be ineffective at detection of malingering (Quinn, 2003). Jachimowicz & Geiselman (2004) found that the falsification rate, or the percentage of students who can successfully malinger on a given instrument, was 65% on the Wender Utah Rating Scale (WURS), 75% on the ADHD Rating Scale IV (ARS), 90% on the Conners Adult ADHD Rating Scale (CAARS), and 95% on the Brown Adult ADHD Scale (BAAS). Fisher & Watkins
(2008) found that 77% and 93% of students successfully faked on the ADHD behavior checklist and the College ADHD Response Evaluation (CARE).

SVTs are the only tools that have been shown to offer moderately good sensitivities toward malingering (Sollman, Ranseen & Berry, 2010). Quinn (2003) found that the Integrated Visual and Auditory Continuous Performance Test (IVA CPT) had sensitivity and specificity above 90%. Rios & Morey (2013) found that the subtle scales such as Negative Impression scale (NIM) and Rogers Discriminant Function (RDF) subscales of the Personal Assessment Inventory (PAI) showed satisfactory sensitivity (64% and 84%, respectively). Marshall et al. (2010) found that combining two or more SVTs, or one SVT and one cognitive test, can offer sensitivities and specificities in the range of 95% and 98% respectively. Harrison, Edwards & Parker (2007) found that malingerers obtained higher scores on the CAARS and lower scores on the Woodcock Johnson Psychoeducational Battery – III (WJPB – III), than individuals who have ADHD, and proposed that these two tests be used in combination to identify malingerers. However, Jasinski et al. (2011) tested a wide range of behavioral rating scales, cognitive tests, and SVTs and found that most students were able to fake their symptoms on the all the scales tested. Though there is a lack of consensus in the literature, some SVTs, and some cognitive tests, may offer adequate sensitivity to malingering. However, their potential is limited by their drawbacks. SVTs and other cognitive performance tests are time consuming, complex, impose heavy respondent burden and often need computerized testing and scoring and require training for interpretation of scores.

1.2 Subtle Scales

Subtlety in scale development is the lack of face validity in the items of a given instrument. It is defined as “degree to which the psychopathological meaning of an item can be determined in
an a priori fashion” (Burkhart, Gynther & Christian, 1978). The disadvantages of SVTS can be overcome by subtle scales. Subtle scales hold an advantage over traditional SVTs in detecting malingering because their lack of face validity makes faking un-intuitive. Most subtle scales suffer from poor sensitivity at detecting malingering of ADHD because they were not specifically developed to detect malingering in the context of ADHD (Musso & Gouvier, 2012). The newly developed subtle scale, the Subtle ADHD Malingering Scale (SAMS), grounded in the Accuracy of Knowledge framework (Lanyon, 1997), was developed for to be a short, simple, and easy tool for administration in the clinical setting to detect malingering of ADHD. This scale was also shown to have acceptable factor validity, reliability, and construct validity (Ramachandran et al., in preparation).

1.3 Objective

This study aims to calculate the sensitivity and specificity of the SAMS to malingering of ADHD and to test its resistance to malingering compared to the PAI.
METHODS

2. Methods

2.1 Study Design

This study employed a cross-sectional, experimental design using a self-administered, computer-based survey distributed to conveniently sampled groups of college-enrolled adults with and without ADHD. The study design and sample were previously explained in detail in Ramachandran et al. (in preparation). Approval was obtained from the University of Mississippi IRB.

2.2 Study Participants and Data Collection

This study sampled from the undergraduate population at the University of Mississippi. Students with ADHD and students without ADHD were both sampled in order to identify the scale’s ability to differentiate individuals who actually have ADHD from those who are malingering symptoms. Respondents were assigned to one of three groups as part of the experimental design. Respondents who self-reported ADHD were instructed to respond to the test item pool honestly; this was called the ADHD group. Respondents who self-reported not having ADHD were randomized to one of two groups where they were either instructed to fake ADHD on the test item pool, called the Malingering group, or instructed to respond honestly, called the Control group. Self-reported ADHD was validated by asking respondents the time
since their ADHD diagnosis, the time spent during ADHD diagnostic visit, and the specialty of
the diagnosing practitioner.

Study recruitment was conducted through a series of announcements conducted in classes
held across the campus of University of Mississippi, in order to obtain a representative sample.
All participants were offered extra course credit as an incentive for participation. Additional
incentives, in the form of a chance to win one out of five $25 gift cards, were offered to
individuals assigned to the Malingerer group in order to match real world incentives for
malingering. Interested students set up appointments with the research team, and completed the
survey in person on a computer assigned to them. The survey was designed using Qualtrics, and
all data were collected anonymously.

2.3 Survey Design

Respondents were asked to indicate their age, gender, ADHD diagnosis, and other
demographic information before responding to the SAMS. To provide a comparator to the
SAMS, the Personality Assessment Inventory – Adult (PAI - A) was administered at the end of
the survey. The PAI was chosen because it contains multiple validity scales such as the Negative
Impression scale (NIM), the Positive Impression Scale (PIM), the Malingering Index (MAL) and
the Rogers Discriminant Function (RDF). These subscales showed satisfactory sensitivity and
specificity toward malingering of ADHD (Rios & Morey, 2013).

2.4 Data Analysis

All data were analyzed using IBM SPSS (Chicago, IL). Demographic characteristics
were compared across all three study groups using t-test and chi square, as appropriate.
2.4.1 Selecting a Cut-off Point

In order to calculate an optimal cut-off point, a combination of ROC curve analysis and CART analysis was used. ROC curve analysis is the most popular technique for estimating an efficient cut-off score for a diagnostic test (Fletcher, Fletcher & Fletcher, 2014). However, the items in the SAMS are expected to have different distributions because they were grounded in different constructs of the Accuracy of Knowledge framework (Lanyon, 1997; Ramachandran et al., in preparation). Using a total scale score of such a combination of items to calculate a cut-off point might cause a loss in the detail of information provided by each type of question. In order to effectively utilize all the subscales of the SAMS to provide a simple, but effective scoring algorithm, Classification and Regression Trees (CART) analysis was also used in the calculation of a cut-off score (Moisen, 2008).

CART analysis is an advanced technique of calculating cut-off points for scales that attempt to distinguish one group of individuals from another (Breiman et al., 1984). It provides results which can be simple, yet powerful and easily visualized, especially in cases where more than two groups might be present in the data (Franck, 2013). Weigel, Meston & Rosen (2005) recommend that a combination of ROC analysis followed by CART analysis be used to estimate cut-off points. Following the estimation of a cut-off score, psychometric indices such as sensitivity, specificity, false positive rate, and false negative rate were calculated. The ability of the scale to resist malingering can be estimated from the falsification rate or the false negative rate.
2.4.2 Comparison with Pre-existing Scales

The comparison of the performance of the SAMS and the PAI was conducted using a concordance & discordance analysis, as used in Myerholtz & Rosenberg (1997). To compare the degree of correspondence between the two screening instruments, a phi coefficient (Cheetam & Hazel, 1969; Kuhn, 1973) and a Cohen’s kappa (Cohen, 1960) were calculated. The McNemar test was also used to compare the sensitivity & specificity of the two scales (Cheetam & Hazel, 1969).
3. Results

3.1 Demographic characteristics

The data collection effort resulted in a total of 637 completed responses. The demographic characteristics of the respondents are presented in Table 1. The respondent sample had a mean age of 20.5 years, was comprised of 63.6% females, 74.1% Caucasians, and 46.9% freshmen. 16.6% (106) of the sample self-reported ADHD, and 12.7% (81) self-reported other mental illnesses. 35.3% of the total sample self-reported misusing prescription stimulants. Eight respondents self-reported attempting to feign ADHD in a physician’s office. These 8 responses were excluded from all subsequent analyses because they did not fit into any one of the three predefined study groups. The breakdown of each of the demographic characteristics across the three study groups is provided in Table C1.
<table>
<thead>
<tr>
<th>Characteristic</th>
<th>ADHD N = 102</th>
<th>Malingers N = 264</th>
<th>Controls N = 259</th>
<th>$\chi^2$</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (Mean [SD]; F)</td>
<td>20.9[2.12]</td>
<td>20.5 [1.68]</td>
<td>20.5</td>
<td>2.38</td>
<td>2, 625</td>
<td>0.093</td>
</tr>
<tr>
<td>Female</td>
<td>51 (49.5)</td>
<td>178 (68.2)</td>
<td>173 (65.5)</td>
<td>11.6</td>
<td>2</td>
<td>0.003</td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td>28.2</td>
<td>12</td>
<td>0.002</td>
</tr>
<tr>
<td>Caucasian</td>
<td>88 (85.4)</td>
<td>175 (67)</td>
<td>201 (75.8)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>African American</td>
<td>6 (5.8)</td>
<td>51 (19.5)</td>
<td>36 (13.6)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic or Latino/a</td>
<td>2 (1.9)</td>
<td>5 (1.9)</td>
<td>0 (0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian or Pacific Islander</td>
<td>2 (1.9)</td>
<td>22 (8.4)</td>
<td>19 (7.2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>American Indian</td>
<td>0 (0)</td>
<td>1 (0.4)</td>
<td>0 (0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Biracial or Multiracial</td>
<td>3 (2.9)</td>
<td>6 (2.3)</td>
<td>8 (3.0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>2 (1.9)</td>
<td>0 (0.4)</td>
<td>1 (0.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Greek membership</td>
<td>62 (60.2)</td>
<td>116 (44.6)</td>
<td>122 (46.0)</td>
<td>7.73</td>
<td>2</td>
<td>0.021</td>
</tr>
<tr>
<td>School year</td>
<td></td>
<td></td>
<td></td>
<td>7.27</td>
<td>6</td>
<td>0.297</td>
</tr>
<tr>
<td>Freshman</td>
<td>42 (40.8)</td>
<td>119 (45.6)</td>
<td>135 (50.9)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sophomore</td>
<td>28 (27.2)</td>
<td>57 (21.8)</td>
<td>62 (23.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Junior</td>
<td>20 (19.4)</td>
<td>60 (23.0)</td>
<td>41 (15.5)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Senior (and above)</td>
<td>13 (12.6)</td>
<td>25 (9.6)</td>
<td>27 (10.2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residence</td>
<td></td>
<td></td>
<td></td>
<td>21.0</td>
<td>10</td>
<td>0.021</td>
</tr>
<tr>
<td>On-campus residence hall</td>
<td>44 (42.7)</td>
<td>123 (47.1)</td>
<td>142 (53.6)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraternity/Sorority house</td>
<td>9 (8.7)</td>
<td>14 (5.4)</td>
<td>10 (3.8)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other on-campus housing</td>
<td>1 (1.0)</td>
<td>12 (4.6)</td>
<td>1 (0.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parent/Guardian home</td>
<td>1 (1.0)</td>
<td>7 (2.7)</td>
<td>3 (1.1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Off-campus housing</td>
<td>48 (46.6)</td>
<td>103 (39.5)</td>
<td>107 (40.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>0 (0)</td>
<td>2 (0.8)</td>
<td>2 (0.8)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected GPA</td>
<td></td>
<td></td>
<td></td>
<td>31.9</td>
<td>6</td>
<td>&lt;0.00</td>
</tr>
<tr>
<td>3.5 to 4</td>
<td>31 (30.1)</td>
<td>122 (46.9)</td>
<td>124 (47.0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 to 3.49</td>
<td>37 (35.9)</td>
<td>107 (41.2)</td>
<td>103 (39)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.5 to 2.99</td>
<td>27 (26.2)</td>
<td>28 (10.8)</td>
<td>30 (11.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 to 2.49</td>
<td>8 (7.8)</td>
<td>3 (1.2)</td>
<td>7 (2.7)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Below 2</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Insurance status</td>
<td></td>
<td></td>
<td></td>
<td>7.15</td>
<td>12</td>
<td>0.848</td>
</tr>
</tbody>
</table>

102
<table>
<thead>
<tr>
<th>Health Insurance</th>
<th>80 (77.7)</th>
<th>181 (69.6)</th>
<th>194 (73.2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private health insurance from parents/family</td>
<td>7 (6.8)</td>
<td>14 (5.4)</td>
<td>15 (5.7)</td>
</tr>
<tr>
<td>Independent private health insurance plan</td>
<td>4 (3.9)</td>
<td>15 (5.8)</td>
<td>14 (5.3)</td>
</tr>
<tr>
<td>Private health insurance from Employer</td>
<td>5 (4.9)</td>
<td>14 (5.4)</td>
<td>13 (4.9)</td>
</tr>
<tr>
<td>No health insurance</td>
<td>2 (1.9)</td>
<td>18 (6.9)</td>
<td>11 (4.2)</td>
</tr>
<tr>
<td>State Medicaid plan</td>
<td>1 (1.0)</td>
<td>8 (3.1)</td>
<td>7 (2.6)</td>
</tr>
<tr>
<td>Medicare plan</td>
<td>4 (3.9)</td>
<td>10 (3.8)</td>
<td>11 (4.2)</td>
</tr>
<tr>
<td>Other</td>
<td>103 (100)</td>
<td>0 (0)</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

ADHD: Attention Deficit Hyperactivity Disorder; SD: Standard Deviation; df: degrees of freedom; GPA: Grade Point Average

### 3.2 Estimation of a Cut-off Score & Psychometric Indices

As seen in Figure 1, the ROC Curve analysis using the total sum scale score of the SAMS was found to provide significant discrimination between the malingerers and the honest respondents, with an area under the curve of 0.901 (Standard error: 0.012; p: < 0.0001). The selected cut-off from the ROC curve analysis was a total SAMS score greater than 27; respondents greater than this score were classified as malingerers. This score offered a sensitivity of 89.2% and a specificity of 77.8%.
The risk estimate for the CART analysis, as seen in figure 2, was 0.239, with a standard error of 0.017. The cutoff score obtained from CART analysis utilized each individual factor score. Respondents were classified as malingerers if their psychological scale score was greater than 15 and the academic scale score was greater than 7. This classification provided a sensitivity of 90.3% and a specificity of 80.1%, both superior to the results of the ROC curve analysis. For the remainder of this study, the classification algorithm from the CART analysis was used for the SAMS scores. Given these values of sensitivity & specificity, the classification algorithm
provided by the CART analysis was found to have a false positive rate of 19.9% and a false negative rate of 9.7%.

**Figure 2: CART Analysis Tree diagram**

The results of the CART analysis can also be used to differentiate all three study groups. The respondents who score less than or equal to 15 on the Psychological factor are comprised of a majority of the Control group, and those scoring greater than 15 on the Psychological factor and less than or equal to 7 on the Academic factor were mostly comprised of the ADHD group. The classification accuracy of the ROC curve analysis and the CART analysis in each study subgroup is provided in Table C2.
Table C2: Classification accuracy of the SAMS and PAI in each study group

<table>
<thead>
<tr>
<th>Scale/Group</th>
<th>ADHD group</th>
<th>Malingerer group</th>
<th>Control group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N (%)</td>
<td>N (%)</td>
<td>N (%)</td>
</tr>
<tr>
<td><strong>ROC curve classification</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Malingerer</td>
<td>56 (56.6)</td>
<td>231 (89.2)</td>
<td>22 (8.7)</td>
</tr>
<tr>
<td>Honest respondent</td>
<td>43 (43.4)</td>
<td>28 (10.8)</td>
<td>231 (91.3)</td>
</tr>
<tr>
<td>Total</td>
<td>99</td>
<td>259</td>
<td>253</td>
</tr>
<tr>
<td><strong>CART classification</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Malingerer</td>
<td>48 (48.5)</td>
<td>234 (90.3)</td>
<td>22 (8.7)</td>
</tr>
<tr>
<td>Honest respondent</td>
<td>51 (51.5)</td>
<td>25 (9.7)</td>
<td>231 (91.3)</td>
</tr>
<tr>
<td>Total</td>
<td>99</td>
<td>259</td>
<td>253</td>
</tr>
<tr>
<td><strong>PAI classification</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Malingerer</td>
<td>14 (15.1)</td>
<td>129 (50.6)</td>
<td>23 (9.2)</td>
</tr>
<tr>
<td>Honest respondent</td>
<td>79 (84.9)</td>
<td>126 (49.4)</td>
<td>226 (90.8)</td>
</tr>
<tr>
<td>Total</td>
<td>93</td>
<td>255</td>
<td>249</td>
</tr>
</tbody>
</table>

**NOTE:** ROC curve classification rule: Total SAMS score greater than 27; CART classification rule: SAMS psychological factor score greater than 15 and SAMS academic factor score greater than 7; PAI classification rule: Negative Impression Scale score greater than 92 or Malingering scale score greater than 3. The “total” provided is the number of completed respondents for each scale, which is different for the PAI and the SAMS.

3.3 Comparator Scale

This study used the PAI as a comparator to the SAMS. The classification rules for the PAI were obtained from previous research identifying malingering of ADHD using the PAI (Rios & Morley, 2013). Rios & Morley (2013) used three rules to classify a PAI respondent as a malingering: a Negative Impression Scale (NIM) score greater than 92, and a Malingering (MAL) scale score greater than 3, and a Roger’s Discriminant Function (RDF) greater than 0. However,
because the RDF was based on a large number of items, each with possible missing values, there were a large number of missing values in the RDF variable; and it had to be dropped from the classification rule. In order to provide the PAI the best chance of identifying malingers, a rule of either an NIM score greater than 92 or a MAL score greater than 3 was used, essentially stacking the odds against the SAMS. Using this classification rule, the PAI provided a sensitivity of 51.0% and a specificity of 89.2%.

The total degree of agreement between the PAI and the SAMS was found to be (417 out of 592) 70.4%. A phi coefficient of 0.455 and a Cohen’s kappa of 0.408 were found for the two scales, indicating a moderate degree of agreement. The McNemar test was also used to compare the sensitivity and the specificity of the two scales. The SAMS was shown to have significantly higher sensitivity (p < 0.0005) and lower specificity (p < 0.0005) than the PAI.
DISCUSSION

4. Discussion

This study provides critical research for the further development of the Subtle ADHD Malingering Scale (SAMS) and builds value for its use in the clinical setting. The study used data collected in the Ramachandran et al. (in preparation) research study to develop a cut-off score for SAMS and estimate its classification accuracy. A combination of ROC curve analysis and CART analysis were used to estimate the cut-off score. The CART analysis classification rule showed moderate improvement over that of the ROC curve analysis in terms of sensitivity and specificity. But the CART analysis is truly superior to the ROC curve analysis because it utilizes separate scoring rules for each of the factors in the SAMS, thereby making it harder to fake. It also provides an opportunity to distinguish all three study groups, instead of merely the malingerer group. This ability can provide advantages in the clinical setting to distinguish the two honest study groups: the ADHD group and the Control group. Attempts to classify all three groups might also provide further confirmation of the ADHD diagnosis in the physician’s office. The multiple cut off scores provided by the CART analysis can also make it harder to ‘coach’ to malingering on the SAMS, because successful malingering will require that the scores fall within a narrower range.

The CART classification rule comes with its own drawbacks. The risk estimate from the CART analysis was found to be 0.239, indicating that 23.9% of the respondent pool was misclassified by this technique. The misclassification rate is highest in the ADHD group at
48.5%. This high false positive rate among ADHD respondents indicates that the results of the SAMS should be interpreted with caution in the clinical setting. Being classified as a ‘malingerer’ by the SAMS at a physician’s office should signal the need for additional testing, or a referral to a specialist, in the case of primary care providers. This recommendation for additional testing can maximize efficiency of resource use by only recommending additional testing or referral in some of the patients reporting ADHD symptoms, instead of all of them.

The comparator scale used in this study, the PAI, contains 348 items and includes a complex scoring algorithm. As such its utility in the physician’s office is limited. Rios & Morley (2013) found that the NIM scale provided a sensitivity and specificity of 64% and 73%, respectively, while the MAL scale provided a sensitivity and specificity of 38% and 81%. This study used a combination of the NIM and the MAL scales to identify malingering and found a sensitivity and specificity of 51% and 89%, respectively. Despite using fewer items, the SAMS showed superiority over the PAI at identifying malingering of ADHD, demonstrating the value of a scale that is tailored toward malingering of ADHD symptoms. The PAI had a significantly higher specificity than the SAMS, but this is caused by the fact that the PAI classifies so few respondents as malingerers (as seen in the high false negative rate), that most of the non-malingerer population was correctly classified.

4.1 Limitations

While demonstrating the potential of the SAMS to address malingering of ADHD, this study carries certain limitations. The data collection for this study was conducted along with the development of the SAMS itself (Ramachandran et al., in preparation). Further research needs to be conducted in diverse populations to test the applicability and generalizability of these results.
The comparability of the malingerer group used in this study to the real world malingerer population is unknown. Psychometric indices such as positive predictive value could not be calculated from this study because of the lack of an accurate estimate of the prevalence of malingering.

4.2 Clinical Implications & Future Research

The SAMS presents immense potential for use in the clinical setting to help identify malingering of ADHD. It is tailored toward malingering of ADHD symptoms, and has demonstrated satisfactory sensitivity, specificity, and high resistance to malingering. Physicians evaluating patients for ADHD are recommended to administer the SAMS, pending further research, to help validate the veracity of the patient’s claims. Patients flagged as ‘maligners’ by the SAMS are recommended for additional testing or referral to a specialist to identify if they truly have ADHD. There is a need for further research testing the SAMS directly in the clinical setting and in diverse populations. There is also a need to develop interventions for patients identified as ‘maligners’ by the SAMS. These individuals may need help for drug dependence and counseling to help them cope with the stressors that have encouraged drug-seeking behavior.
BIBLIOGRAPHY


Fletcher, R. H., Fletcher, S. W., & Fletcher, G. S. (2012). *Clinical Epidemiology: The Essentials*. Lippincott Williams & Wilkins.


CHAPTER 5

SUMMARY, CONCLUSIONS, AND FUTURE RESEARCH
CONCLUSIONS

This dissertation explores a growing problem in society with regard to prescription drugs. The study was unique in that it chose to focus on prescription stimulants, rather than the opioids which has been the focus of most recent research in this field of study. This dissertation is the first study of its kind to attempt to address the issue of prescription stimulant abuse by developing techniques to identify individuals attempting to inappropriately access stimulants.

Two different techniques were explored in this study: the first used administrative claims data to classify individual stimulant users using a latent class analysis; and the second attempted to develop a short subtle scale called the Subtle ADHD Malingering Screener (SAMS) for administration in the primary care provider’s office to identify individuals malingering symptoms of ADHD with the intentions of obtaining prescriptions of stimulants for misuse or diversion.

The specific goal of this dissertation was to help develop strategies that can be used in the prevention of abuse of prescription psychostimulants. The combination of techniques developed/tested in this dissertation provide a health policy analyst with tools, such as the SAMS, and the prescription claims based latent classes, required to develop these strategies. These tools still need several rounds of further research before they can be used in strategies tailored for drug abuse prevention, but this dissertation will hopefully serve as the platform for the development and refinement of these tools. The conclusions from each of the three papers are
discussed below, along with directions for future research and the clinical implications of this dissertation.

Concluding Comments on Paper One

This paper developed a deeper understanding of the differences in stimulant use behaviors between abusers and non-abusers, using a latent class analysis to first classify individuals according to their behaviors. It is one of the first studies to attempt to exclusively characterize stimulant use behaviors, and validate the developed latent classes using stimulant abuse diagnoses identified from administrative claims data. The use of administrative claims data to identify misusers of prescription stimulants revealed critical insights that can help future research in this area. This study was also the first to use a combination of Medicaid administrative claims data and PMP data to comprehensively capture all use of stimulants while estimating the risk behaviors.

This study developed a 2-class model with 4.1% of the sample in the one class, and 95.9% of the sample in the other class. The 2-class model, however, was not predictive of a diagnosis of dependent or nondependent stimulant abuse. It is possible that many individuals classified in Class 1 were in fact abusing prescription stimulants, but had not been diagnosed; Unfortunately, there was no way to know their true misuse status from the data. Hence the findings of the prediction of stimulant misuse using latent classes need to be treated with caution. It is possible that alternative validation mechanisms with more reliable identification of misusers might have discovered a correlation with the latent classes obtained in this study. It is possible that any combination of these reasons was responsible for the non-significant finding obtained in this study. The latent classes obtained in this study might still be indicative of stimulant misuse,
but further research into the stimulant use behavior, perhaps using alternative validation techniques, is needed. This study demonstrated the value of latent class techniques to help identify variations in patterns of stimulant use, while also displaying the limitations of administrative claims databases in capturing true misuse status.

Concluding comments on Paper Two

This study is the first of its kind to attempt to develop a scale to identify malingering in the context of ADHD. A ten-item, two-factor solution was obtained for the SAMS in this study. The sum scale score was used to calculate the total score for the SAMS in order to preserve ease of scoring, and reduce time of administration in the physician’s office. Each individual SAMS item was also found to significantly differentiate all three groups in the study, and not just the ADHD group and the Malingerer group. The mean scores on both the psychological and academic factor follow patterns predicted in the Accuracy of Knowledge framework.

The SAMS presents an innovative approach to identify malingering of ADHD symptoms, reduce overdiagnosis of ADHD, and for early identification of prescription stimulant abuse directly in the clinical setting. It is designed to be short, inexpensive, and does not need additional training for administration, scoring, or evaluation, which makes it a valuable resource for primary care providers. There is a need to focus on the needs of malingerers identified by this scale, and to develop interventions that can help malingerers cope with their stressors and address potential addiction problems. Finally, this study successfully demonstrates the methodology of developing a subtle scale with the application of a theoretical framework for item development. This technique can be applied in other areas in such as the early identification
of opioid abusers, injection drug users, to implement early targeted interventions. Further research required on the SAMS was conducted as part of paper three, as presented below.

Concluding comments on Paper Three

This study provides critical research for the further development of the Subtle ADHD Malingering Scale (SAMS) and builds value for its use in the clinical setting. The study used data collected in paper two to develop a cut-off score for SAMS and estimate its classification accuracy. Using CART analysis, a cut off score was developed for the SAMS. Respondents were classified as malingerers if their psychological subscale score was greater than 15 and the academic subscale score was greater than 7. This classification provided a sensitivity of 90.3% and a specificity of 80.1%. The SAMS also showed significantly higher sensitivity than the PAI. Being classified as a ‘malingering’ by the SAMS at a physician’s office should signal the need for additional testing, or a referral to a specialist, in the case of primary care providers.

The SAMS presents immense potential for use in the clinical setting to help identify malingering of ADHD. It is tailored toward malingering of ADHD symptoms, and has demonstrated satisfactory sensitivity, specificity, and high resistance to malingering. Physicians evaluating patients for ADHD are recommended to administer the SAMS, pending further research, to help validate the veracity of the patient’s claims. Patients flagged as ‘malingering’ by the SAMS are recommended for additional testing or referral to a specialist to identify if they truly have ADHD. There is a need for further research testing the SAMS directly in the clinical setting and in diverse populations. There is also a need to develop interventions for patients identified as ‘malingering’ by the SAMS. These individuals may need help for drug dependence and counseling to help them cope with the stressors that have encouraged drug-seeking behavior.
IMPLICATIONS

Implications for Research & Practice

This dissertation was carried out with the goal of making a change in the healthcare system that contributes to millions of cases of prescription stimulant abuse every year. The latent classes developed in paper one, with further refinement, can provide a tool to payers such as commercial insurance companies or Medicaid to help identify individuals who are in need of intervention for drug abuse, and to help curtail others who may be diverting their prescriptions. Once the identification of these individuals can be accomplished with reasonable accuracy, tailored interventions need to be developed that involve a combination of lock-in programs to prevent further drug diversion, and medical intervention to help treat possible drug abuse problems. Further research is needed to develop validation tools that can estimate if latent classes using behavioral risk factors can perform reliably at identifying individuals who are misusing or diverting stimulant prescriptions.

Papers two and three serve a different purpose in the prevention of drug abuse. They used a college student population, to help develop a tool for use in the physician’s office to help identify malingerers of ADHD symptoms. This can help address overdiagnosis of ADHD, and over-prescribing of stimulants. The SAMS displayed potential for clinical use with high levels of sensitivity and specificity. A true estimate of prevalence of malingering in various settings needs to be estimated to calculate a positive and negative predictive value that can help direct recommendations for the individuals identified by SAMS. Further testing in other populations
including children under the age of 18 years, and adults not enrolled in colleges is required before the SAMS can be recommended in the clinical setting.


Fortuna, R. J., Robbins, B. W., Caiola, E., Joynt, M., & Halterman, J. S. (2010). Prescribing of controlled medications to adolescents and young adults in the United States. Pediatrics,


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EDUCATIONAL QUALIFICATIONS:

- Currently pursuing a PhD in the Department of Pharmacy Administration at the University of Mississippi, University, MS. (Expected completion: December, 2016)
  - Dissertation:
    - Identification Of Stimulant Misuse & Malingering Of ADHD
  - Advisor: Dr. John P. Bentley
- Master of Science in Pharmacy Administration (2011 – 2014) at the University of Mississippi, University, MS.
  - Thesis Project: Determining The Physician And Patient Characteristics Influencing The Use Of Atypical Antipsychotics In Children
  - Advisor: Dr. Benjamin F. Banahan
- Bachelor of Pharmacy (2007 – 2011) at Osmania University, Hyderabad, India.

RESEARCH SKILLS:

- Survey design, data collection & management, analysis
- Survey development using Qualtrics™
- Qualitative research design and analysis
- Big data analysis
- Multivariate Statistical analysis
- Programming skills:
  - SPSS*
  - SAS*
  - Visual Basic for Applications (VBA), for Excel
- Model development and analysis using TreeAge® Pro suite
- Microsoft® Office suite
RESEARCH EXPERIENCE:

- Conjoint study design, and patient simulation techniques
- Designing & conducting physician & patient surveys
- In-Depth Interviews with family practitioners, pharmacists, specialists, and patients
- Moderating focus groups of practitioners, patients, and pharmacists
- Model building such as: budget impact models, cost effectiveness models
- Statistical techniques such as: Multivariate data analysis, and longitudinal data modelling
- Design and analysis of transaction claims data

WORK EXPERIENCE:

  - **Mississippi Medicaid**, Drug Utilization Review team:
    - Analysis of Mississippi Medicaid claims data
    - Research design and analysis
    - SAS® programming to answer questions relevant to policy decisions
- **Marketing Intern, Bavarian Nordic Immunotherapeutics**, Mountain View, CA (June – August, 2013)
  - Physician participation in prostate cancer clinical trials: A primary research study assessing motivators, barriers, contact strategies, product ratings and perceptions of clinical trials in advanced prostate cancer
  - Competitive landscape analysis and market overview
    - Health economic and analogue analysis

ACADEMIC EXPERIENCE:

Publications:

- **Ramachandran S**, Banahan BF, Bentley JP, West DS, Patel A. Factors Influencing the Use of Atypical Antipsychotics in Children with Psychosis. *Journal of Managed Care Pharmacy*. Accepted for publication.

**Posters:**

- **Ramachandran S**, Mahabaleshwarkar R, Yang Y. Cost Consequence Analysis Of Telaprevir Versus Boceprevir For The Treatment Of Previously Untreated Chronic Hepatitis-C Virus Infection. Meeting in the Middle, Austin, TX, June 2012.

**COURSEWORK:**

- **Research techniques**: Research Methods, Primary Data Techniques, Secondary Data Techniques, Data Management and Statistical Software (SAS®)
- **Health care landscape**: Pharmacoeconomics, Pharmaceutical and Health Care Policy, Health Economics, Pharmacoepidemiology, Advanced Pharmaceutical Marketing & Patient Behavior
- **Marketing**: Drug Development and Marketing, Marketing theory, Consumer behavior, Quantitative Methods in Psychology, Marketing strategy, Customer Relationship Management
- **Statistics**: Quantitative Methods in Psychology, General Linear Models, Applied Multivariate analysis, Mediation and Moderation
MANUSCRIPT REVIEW:

- Occasional Reviewer for *Currents in Pharmacy Teaching and Learning*
- Occasional Reviewer for *Aging and Mental Health*

AWARDS:

- Best podium presentation award at Southern Pharmacy Administration Conference, Oxford, MS, June 2016.
- Best poster award at American Pharmacists Association (APhA) Annual Meeting & Exposition, Baltimore, MD, March 2016.
- Graduate Achievement Award, 2015 – 16 and 2015 Honors day program nominee.
- UM Phi Kappa Phi Academic Honors society scholarship, 2015 – 16.
- Terrence E. Downer Marketing Scholarship, 2015 – 16.
- Winner of the inaugural National Case Study Contest and invitee to the Pharmaceutical Marketing Research Group (PMRG) Annual meeting in Philadelphia, PA, October 2015.

3 Minute Thesis competition:
  - Grand Prize Winner, and University of Mississippi represent at the Conference of Southern Graduate Schools (CSGS) 2015.
  - People’s Choice Award at CSGS, March 2015, New Orleans, LA.

School of Pharmacy Teaching Assistant of the years 2012-2013, and 2013-2014.

“Who’s Who Among Students in American Universities and Colleges” at the University of Mississippi, 2013-14.

- Phi Kappa Phi academic honors society, 2013 initiate.
- Best presentation for a poster titled ‘Oncolytic Viruses’ presented at a national conference, Hyderabad, India.

Academic scholarship:

PROFESSIONAL CITIZENSHIP:

- International Society of Pharmacoeconomics and Outcomes Research (ISPOR; 2011 – Present)
  - President of UM ISPOR Student Chapter (2015-16)
  - Member of the ISPOR National Education subcommittee (2014-15)
  - Vice-President UM ISPOR Student Chapter (2014-15)
  - Secretary UM ISPOR Student Chapter (2012-13)

- Pharmaceutical Marketing Research Group (PMRG; 2011 – Present)
  - Member of the National PMRG Institute Academia subcommittee (2014 – Present)
  - Member of the National PMRG Institute Membership subcommittee (2015 – Present)
  - President of UM PMRG Student Chapter (2014-15)
  - Vice President of UM PMRG Student Chapter (2013-14)
- University of Mississippi Graduate Student Council (2011 – Present)
  - Vice President (2013-14)
  - Member of the Chancellor’s committee on Graduate Council (2013-14)
  - Member of the Vice Chancellor’s committee on Student Affairs (2013-14)
  - Senator for the department of Pharmacy Administration in the University of Mississippi Graduate Student Council (2012-13).
  - Chair of the Graduate Student Council Rules sub-committee (2012-13).
- Phi Kappa Phi Academic Honor society (2013-16).
- Who’s Who society at the University of Mississippi (2013-14).
- University of Mississippi Indian Student Association (2011 – Present)
  - Vice President (2011-12)