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DEFINING PROBLEMATIC SCHOOL ABSENTEEISM USING NONPARAMETRIC MODELING

By

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Bachelor of Arts - Psychology
Hope College
2013

Master of Arts - Psychology
University of Nevada, Las Vegas
2015

A dissertation submitted in partial fulfillment
of the requirements for the

Doctor of Philosophy - Psychology

Department of Psychology
College of Liberal Arts
The Graduate College

University of Nevada, Las Vegas
December 2017

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Dissertation Approval

The Graduate College
The University of Nevada, Las Vegas

November 3, 2017

This dissertation prepared by

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Defining Problematic School Absenteeism Using Nonparametric Modeling

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ABSTRACT

Defining Problematic School Absenteeism Using Nonparametric Modeling

by

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Contemporary classification models of school absenteeism often employ a multitier approach for organizing assessment and treatment strategies. Researchers have yet to agree, however, on how to objectively define problematic school absenteeism and identify demarcation points for each tier. The present study aimed to inform a multitier approach by determining the most relevant risk factors for problematic school absenteeism. The most useful targets of assessment for problematic school absenteeism are also addressed. The present study examined problematic school absenteeism defined at three distinct cutoffs: 1%, 10%, and 15% of full school days missed. The present study evaluated interactions among several youth- and academic-related variables at each cutoff. Participants included 316,004 elementary, middle, and high school youth from the Clark County School District of Nevada. The present study examined all youth regardless of their school absenteeism. The present study employed Binary Recursive Partitioning (BRP) techniques to identify the most relevant risk factors and highlight profiles of youth exhibiting school absenteeism at each cutoff by constructing classification trees. BRP, a nonparametric statistical approach, is most appropriate for generating, not testing, hypotheses. Anticipated findings were thus offered cautiously. The first hypothesis was that participation in school sports would produce the greatest impurity reduction in the

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classification tree-model for problematic school absenteeism, defined as equal to or greater than 1% of full school days missed. The second hypothesis was that grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), and GPA would produce the greatest impurity reductions in the classification tree-model for problematic school absenteeism, defined as equal to or greater than 10% of full school days missed. The third hypothesis was that age, gender, and ethnicity would produce the greatest impurity reductions in the classification tree-model for problematic school absenteeism, defined as equal to or greater than 15% of full school days missed. Models were constructed via Classification and Regression Tree (CART) analysis utilizing SPSS decision tree software. The first hypothesis was not supported but the second and third hypotheses received partial support. Results revealed age, ethnicity, gender, GPA, grade level, and IEP eligibility as relevant risk factors for problematic school absenteeism among the three cutoffs. Implications for clinicians and educators are discussed.

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ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Christopher Kearney, for his continued guidance, support, and patience throughout this process. I would also like to thank Drs. Paul, Freeman, and Coughenour, my committee members, for their valuable contributions to this project. I greatly appreciate the hard work of the directors and staff at the Clark County School District (CCSD) Assessment, Accountability, Research, and School Improvement Department and their willingness to collaborate with the School Refusal Research Laboratory. I am especially grateful to my husband, Adam, and son, Dempsey, for their unconditional love and support. Finally, thank you to my parents, Mark and Katherine, who have always pushed me to achieve my goals.

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CHAPTER 1

INTRODUCTION

School absenteeism refers simply to a youth's absence from school (Kearney, 2016). Absences come in different forms and range from occasional tardiness to many full days of school missed (Hansen, Sanders, Massaro, & Last, 1998). Most instances of school absenteeism are temporary and nonproblematic (Hersov, 1985) but frequent or prolonged absences can become troublesome for a youth and his/her family. Little consensus has emerged, however, on the best way to distinguish nonproblematic and problematic school absenteeism. A detailed overview of the varying definitions of school absenteeism thus follows.

Nonproblematic and Problematic Absenteeism

Nonproblematic school absenteeism often involves parent-school official agreement that an absence is legitimate and not harmful (Kearney, 2016). Legitimate absences may include illness, family emergencies, and hazardous weather conditions. Nonproblematic absenteeism also includes self-corrective behavior, as when a youth misses a small amount of school time but then returns promptly and with minimal assistance from school personnel (Kearney, 2008b). A key aspect of nonproblematic school absenteeism is that youth do not experience profoundly negative academic or social consequences as a result of the absence.

Definitions of problematic school absenteeism tend to focus on behaviors that significantly interfere with academic progress and the actual amount of school time missed, regardless of whether an absence has been authorized (Kearney, 2016). For example, a youth may miss multiple days of school due to a family funeral but still

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experience reductions in test scores and difficulty reintegrating with peers. A key aspect of problematic school absenteeism is that youth exhibit academic or social problems as a result of the absence.

Researchers and agencies have proposed a number of cutoffs based on the percentage of school time missed (e.g., 1%, 10%, or 15%) to define problematic school absenteeism more concretely. Egger and colleagues (2003) utilized the smallest of these cutoffs when examining hundreds of absentee youth. Youth had to have been absent only one-half day of school in a 3-month period to be included in the study. This translates to less than 1% of school time missed. The U.S. National Center for Education Statistics (NCES) defines chronic absenteeism as missing at least 15 days of school throughout the academic year (NCES, 2016a). This translates to approximately 10% of school time missed. Ingul and colleagues (2012) utilized the highest of these cutoffs when examining hundreds of absentee youth. Youth had to have been absent from school at least 13.5 days in the first term of the academic year to be categorized as “high absence.” This translates to 15% of school time missed. Skedgell and Kearney (2016) also suggested a 15% cutoff for problematic school absenteeism after examining absentee youth categorically at multiple severity levels.

Researchers have not determined which cutoff is best for distinguishing nonproblematic and problematic school absenteeism. Numerous studies have revealed that negative consequences may arise at each distinction (Egger, Costello, & Angold, 2003; Ingul, Klockner, Silverman, & Nordahl, 2012; NCES, 2016a; Skedgell & Kearney, 2016). A majority of contemporary classification models of school absenteeism, however, rely on a cutoff to develop their multi-tiered frameworks. The next section thus

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details one such model, the Multi-Tiered System of Supports (MTSS), and how the present study aimed to better inform the distinction of tiers and assessment targets of this approach.

Multi-Tiered System of Supports

Multi-Tiered System of Supports (MTSS) is a contemporary evidence-based model of school instruction and intervention delivered to youth in varying intensities. The model utilizes data-based approaches to solve problems such as school absenteeism (Kearney & Graczyk, 2014). MTSS hierarchically arranges assessment and treatment strategies for school absenteeism into preventative (Tier 1), targeted (Tier 2), and intensive (Tier 3) categories (Figure 1). A main focus of the present study was to determine the best way to concretely distinguish Tier 1 and Tier 2 by evaluating the most relevant risk factors for problematic school absenteeism. The present study also determined useful assessment methods for problematic school absenteeism for clinicians and educators.

Tier 1 strategies, or universal assessment and intervention, address all youth regardless of their attendance. These universal strategies are intended to focus on the prevention of school absenteeism at a broad level. This tier is thus directed at youth with nonproblematic school absenteeism who have not yet reached a predetermined cutoff (e.g., 1%, 10%, or 15% of full school days missed) for problematic school absenteeism. Tier 1 assessment strategies may involve daily monitoring and record keeping of actual absences, both excused and unexcused (Kearney & Graczyk, 2014). Tier 1 assessment strategies also include surveying youth to determine strengths and weaknesses with respect to school climate or the general quality of school life (Kearney, 2016). Tier 1

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intervention strategies involve school-wide efforts to improve the safety, physical and mental health, and socio-emotional functioning of a youth, as well as parental involvement (Kearney & Graczyk, 2014).

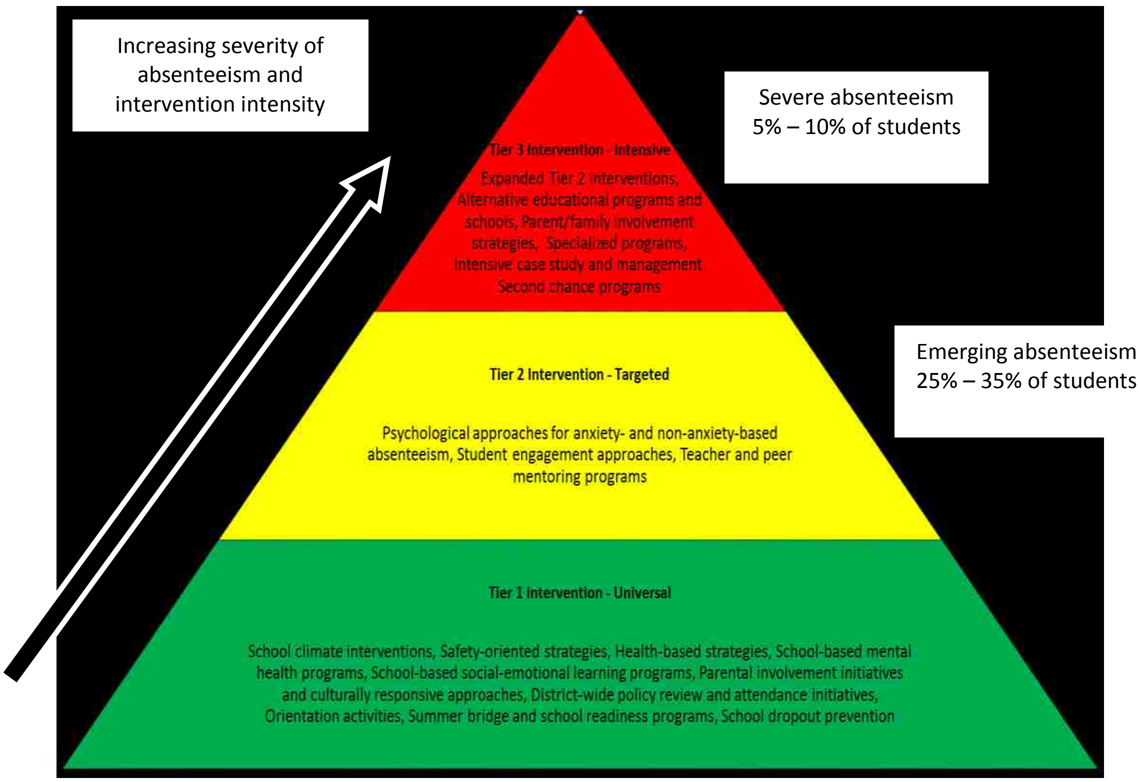

Figure 1. A multitier model for problematic school absenteeism. Reprinted from "Managing school absenteeism as multiple tiers: An evidence-based and practical guide for professions" by C. A. Kearney, 2016, New York: Oxford University Press. Copyright 2016 by the Oxford University Press. Reprinted with permission.

Tier 2 strategies, or targeted assessment and intervention, address youth with emerging school absences. These targeted strategies are intended to focus on at-risk youth that require additional support beyond universal strategies (Sailor, Doolittle,

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Bradley, & Danielson, 2009). This tier is thus directed at youth with problematic school absenteeism that has reached a predetermined cutoff (e.g., 1%, 10%, or 15% of full school days missed). Tier 2 assessment strategies involve interviewing a youth and other relevant individuals such as parents, peers, and school officials to further determine the form, function, and consequence of the youth's school absenteeism (Kearney & Graczyk, 2014). Other targeted assessment strategies involve questionnaires, behavioral observations, academic record review, and formal testing (Kearney, 2016). Tier 2 intervention strategies usually involve multidisciplinary efforts to improve a youth's psychological functioning and re-engagement with school (Kearney & Graczyk, 2014).

Tier 3 strategies, or intensive assessment and intervention, address youth with severe problematic school absenteeism. These intensive strategies focus on youth with chronic patterns of absenteeism that require considerable efforts to address (Kearney, 2016). This tier is thus directed at youth who have long surpassed a predetermined cutoff for problematic school absenteeism (e.g., 1%, 10%, or 15% of full school days missed). Tier 3 assessment strategies may involve individual case study analysis with input from multiple systems and evaluations (Kearney & Graczyk, 2014). Tier 3 intervention strategies may involve expanded Tier 2 interventions and alternative educational programs, among other methods (Kearney, 2016).

MTSS is particularly applicable to school absenteeism for several reasons. A key advantage is early identification and intervention with progress monitoring (Kearney & Gracyzk, 2014). The model thus requires intervention prior to problematic school absenteeism. This is especially important for school absenteeism because even a small amount of absences can result in negative consequences (Egger et al., 2003). MTSS also

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utilizes functional behavioral assessment. Functional analysis emphasizes the identification of maintaining variables for school absenteeism to align interventions accordingly (Kearney & Graczyk, 2014).

MTSS includes empirically supported treatment procedures that emphasize problem solving and shaping targeted interventions to minimize barriers to academic achievement such as absenteeism (Jimerson, Burns, & VanDerHeyden, 2007). The model is also compatible with other multitier approaches and may be more familiar to educational professionals working with absentee youth (Kearney & Graczyk, 2014). This is advantageous because MTSS requires a team-based approach for proper implementation. Team members may include school-based professionals, parents, peers, community-based medical and mental health professionals, and legal personnel such as lawyers and police, and juvenile detention and probation officers (Richtman, 2007).

MTSS served as a theoretical framework for the present study. The present study aimed to inform the multitier approach by helping distinguish Tier 1 and Tier 2 and by determining useful targets of assessment for problematic school absenteeism. The present study intended to accomplish these objectives by examining risk factors for problematic school absenteeism in a large, gender-balanced, and ethnically diverse sample of community youth. School absenteeism was evaluated at three distinct cutoffs: 1%, 10%, and 15% of full school days missed. Youth-related risk factors included age, gender, and ethnicity. Academic-related risk factors included grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), and grade point average (GPA). Other academic-related risk factors included whether or not a youth was eligible

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to receive an Individualized Education Plan (IEP) during the 2015-16 academic year and whether or not a youth participated in school sports during the 2015-16 academic year.

The present study was the first to employ nonparametric recursive partitioning techniques to identify subgroups of youth at the highest risk for problematic school absenteeism at three distinct cutoffs. Risk factors identified at each cutoff revealed characteristic differences in the subgroups of youth as absenteeism becomes problematic (i.e., moves from Tier 1 to Tier 2). The identified risk factors helped to determine useful targets of assessment for problematic school absenteeism for clinicians and educators.

Further exploratory analyses were conducted by employing CART at different developmental levels (i.e., elementary vs. middle vs. high school). Childhood development encompasses the physiological, cognitive, emotional, & social changes that occur from birth through adolescence such as maturation in the prefrontal brain regions, greater flexibility in thinking, an increased ability to self-regulate, and the transition from primarily parental influence to an interaction of parent- and peer-guidance (Barrett, Fox, Morgan, Fidler, & Daunhauer, 2013; Brown, & Bakken, 2011; Munakata, Snyder, & Chatham, 2012). Research indicates that childhood development has a significant impact on a youth's educational experience (Spodek, & Saracho, 2014). Specifically, the transitions that occur from birth to adolescence may affect a youth's school readiness (Blair, 2002; Raver, 2003), academic performance (Martin, & Ochsner, 2016; Steinberg, Lamborn, Dornbusch, & Darling, 1992), and school adjustment (Ladd, 1990; Schonert-Reichl et al., 2015).

School absenteeism is another educational outcome that may be impacted by a youth's development, particularly during adolescence. Adolescence is a critical period in

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which youth experience the opportunity to self-construct an academic identity that is committed to learning (Skinner & Pitzer, 2012). However, youth are also more vulnerable to declines in academic motivation and achievement during this period (Schulenberg, 2006). Evidence suggests that 40%–60% of youth show signs of disengagement (e.g., uninvolved, apathetic, not trying very hard, and not paying attention) as they progress through secondary school (Steinberg, Brown, & Dornbusch, 1996). Youth who are disengaged from school are at a greater risk for academic failure and school dropout (Li & Lerner, 2011). The present study thus examined whether the most relevant risk factors identified at each cut off (1%, 10%, and 15% of full school days missed) differed based on a youth's developmental level (e.g., elementary vs. middle vs. high school).

The following chapter reviews the literature on school absenteeism in youth. The various terminology, prevalence, and general course of the phenomenon are provided, with an emphasis on risk factors. Classification models of school absenteeism are also discussed in detail. The chapter concludes with a discussion of BRP in medical and psychological research and its advantages over traditional parametric approaches for identifying highest risk subgroups in diverse populations.

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CHAPTER 2

LITERATURE REVIEW

Terminology

School absenteeism is an interdisciplinary field with researchers in education, psychology, social work, criminal justice, law, sociology, nursing, and medicine, among others. Many terms have thus been used to describe the phenomenon and a standardized set of terminology is lacking (Kearney, 2016) (Table 1). A major advantage of a multi-tiered approach to school absenteeism, such as MTSS, is its applicability to all youth, regardless of the severity of their absences. MTSS thus encompasses all absenteeism-related terms outlined in the remainder of this section.

Truancy. Truancy generally refers to school absenteeism where a youth is deliberately spending time away from school without parental knowledge (Bond, 2004; Fremont, 2003; Shdaimah, Bryant, Sander, & Cornelius, 2011; Teasley, 2004). Youth who are truant often openly acknowledge their dislike of school and fabricate excuses for their absences (Thambirajah, Grandison, & De-Hayes, 2008). Youth who are truant also rarely exhibit anxious distress or somatic complaints (Pilkington & Piersel, 1991). Truancy is thus sometimes referred to as non-anxiety-based absenteeism (Fremont, 2003). Other key defining features of truancy include poor motivation and academic progress, lower intelligence, unwillingness to conform to expectations, family conflict and disorganization, and homelessness and poverty (Fremont, 2003; Kearney, 2001; Pilkington & Piersel, 1991; Williams, 1927).

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Table 1

Key Terms Related to Problematic School Absenteeism

Term	Definition
Truancy	Illegal, unexcused absence from school; the term is sometimes applied to youth absenteeism marked by surreptitiousness, lack of parental knowledge or child anxiety, criminal behavior and academic problems, intense family conflict or disorganization, or social conditions such as poverty
School Phobia	Fear-based absenteeism, as when a child refuses school due to fear of some specific stimulus such as a classroom or fire alarm
Separation Anxiety	Excessive worry about detachment from primary caregivers and reluctance to attend school (or, in parents, excessive worry about detachment from the child)
School Refusal	Anxiety-based absenteeism, including general and social anxiety, and general emotional distress, sadness, or worry while in school (also referred to as psychoneurotic truancy)
School Refusal Behavior	Child-motivated refusal to attend school or difficulty remaining in classes for an entire day, whether fear/anxiety related or not

Note. Descriptive note. Adapted from "Managing school absenteeism as multiple tiers: An evidence-based and practical guide for professions" by C. A. Kearney, 2016, New York: Oxford University Press. Copyright 2016 by the Oxford University Press. Adapted with permission.

School Phobia. Johnson and colleagues (1941) first coined the term school phobia to describe school absenteeism marked by anxiety and phobic symptomatology. Later researchers expanded the concept to include distress and a general anxiety-based reluctance to attend school (Waldfogel, Coolidge, & Hahn, 1957). Common sources of school-based anxiety include interacting with peers, speaking in front of the class, or attending an assembly (Thambirajah, Grandison, & De-Hayes, 2008). Other common

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examples of specific school-related objects or situations include buses, tests, teachers, and school administrators (Dumas & Nilsen, 2003; Kearney, 2001).

Separation Anxiety. Separation anxiety involves "developmentally inappropriate and excessive fear or anxiety concerning separation from those to whom the individual is attached" (American Psychiatric Association (APA), 2013, pg. 190). One symptom of separation anxiety disorder in youth is persistent reluctance or refusal to go to school because of fear of separation (APA, 2013). Youth with separation anxiety exhibit distress when required to leave their homes or significant others, both of which are necessary components of regular school attendance.

School Refusal. School refusal refers to anxiety-based absenteeism, including panic and social anxiety, and general emotional distress or worry while going to or at school (Suveg, Aschenbrand, & Kendall, 2005). A common characteristic of school refusal is somatic symptoms such as nausea, vomiting, diarrhea, shaking, sweating, and difficulties breathing (Kearney, 2001). One of the prominent features of youth with school refusal is that, if a decision has been made that the youth will not attend school, then the youth will exhibit a significant recovery in their emotional distress and somatic symptoms (Thambirajah, Grandison, & De-Hayes, 2008).

School Refusal Behavior. School refusal behavior is an umbrella term used to describe child-motivated refusal to attend school and/or difficulties remaining in class for an entire day in youth aged 5-17 years (Kearney & Silverman, 1996). School refusal behavior is typically viewed along a spectrum of attendance problems. The continuum of concerns includes youth who attend school with great dread and somatic complaints that precipitate pleas for future nonattendance, youth who display severe morning

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misbehaviors in an attempt to refuse school, youth who miss sporadic periods of school time, and youth who miss long periods of school time (Figure 2) (Kearney & Bates, 2005).

---X--------------X---------------X--------------X-------------X-------------X-------------X---

School attendance under duress and and pleas for non-attendance	Repeated misbehaviors in the morning to avoid school	Repeated tardiness in the morning followed by attendance	Periodic absences or skipping of classes	Repeated absences or skipping of classes mixed with attendance	Complete absence from school during a certain period of the school year	Complete absence from school for an extended period of time

Figure 2. Continuum of school refusal behavior based on attendance.

A key characteristic of youth with school refusal behavior is the heterogeneity of internalizing and externalizing behavior problems (Kearney, Lemos, & Silverman, 2004). Common internalizing problems include fear, somatic complaints, clinging to caregivers, and general and social anxiety (Kearney, 2001). Other difficulties may include fatigue, depression, and suicidality (Stroobant & Jones, 2006). Common externalizing problems include temper tantrums while being dropped off at school, noncompliance to parent and teacher commands, defiance, aggression, and running away from home or school (Kearney, 2001).

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Epidemiology

The overall prevalence of school absenteeism has been suggested to be greater than most childhood mental disorders (Kearney, 2008a). Kearney (2001) estimated that 5-28% of youth display an aspect of school absenteeism at some point. The exact prevalence of school absenteeism is difficult to estimate due to varying definitions and multiple components such as tardiness and skipped class periods. The remainder of this section will thus focus on prevalence rates for simple school absenteeism, or full days missed from school, for clarity and consistency with the present study.

The NCES reported that 13% of the nation's youth missed 15 or more days of school in the 2013-2014 academic year (NCES, 2016a). This translates to 1 in 8 students that were not present for at least 8% of classroom instruction throughout the academic year. In addition, nearly 500 school districts nationwide reported that 30% or more of youth missed at least 3 weeks of school in the 2013-2014 academic year (NCES, 2016a). Chronic school absenteeism, defined as missing at least 10% (or 18 full days) of school in an academic year, is estimated to be approximately 14-15% (Kearney, 2016). This translates to 5.0-7.5 million youth in the United States that are not regularly attending school. About 25% of these youth are considered severely chronically absent, defined as missing at least 2 months of school during the academic year (Balfanz & Byrnes, 2012).

Simple school absenteeism rates may vary across geographic locations. For example, the West region (i.e., Washington, Oregon, California, Nevada, Idaho, Vermont, Utah, Wyoming, and Colorado) reportedly has more school absenteeism than any other of the nation's regions (NCES, 2016a). The prevalence rates of simple school absenteeism may also differ within these geographic locations depending on school type.

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Research suggests that absenteeism rates are lowest among rural elementary schools, while rates rise substantially in public, inner-city, and larger schools (Kearney, 2001; Teasley, 2004).

Data from the National Assessment of Educational Progress (Ginsburg & Chudowsky, 2012) reveal that rates of school absenteeism have remained stable over the past 20 years. School absenteeism continues to be one of the most serious issues for secondary schools across the nation (Jenkins, 1995; Teasley, 2004). The rate of simple school absenteeism deemed problematic, however, varies depending on location. A key advantage of a multi-tiered approach to school absenteeism, such as MTSS, is its compatibility with different district- and school-wide policies. Rates of school absenteeism may be further understood by reviewing the general progression of attendance-related concerns. The next section thus outlines the course of school absenteeism.

Course

The course of school absenteeism may be categorized as self-corrective, acute, or chronic based simply on the duration of the problem (Kearney & Silverman, 1996). Self-corrective school absenteeism refers to youth whose initial absenteeism remits spontaneously within a 2-week period (Kearney, 2001). Youth often have difficulty adjusting to school but such reluctance generally remits spontaneously or is readily handled by the youth's parents or school administration in up to 25% of cases (Kearney & Tillotson, 1998). Acute school absenteeism refers to youth whose absenteeism lasts 2-52 weeks (Kearney, 2001). Acute school absenteeism often lies undetected before becoming more entrenched (Reid, 2005). Chronic school absenteeism refers to youth

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whose absenteeism lasts longer than 1 calendar year (Kearney, 2001). Youth may exhibit difficulties attending school 1-2 years prior to remediation and approximately 40% of youth may exhibit school absenteeism for longer than 2 years (Kearney & Bates, 2005). Youth with chronic, unaddressed school absenteeism are subject to several negative consequences. Short- and long-term effects of school absenteeism are thus discussed below.

Effects of School Absenteeism

Short-term effects of school absenteeism include academic performance decline, social alienation, and family distress and conflict (Kearney, 2007). Youth with school absenteeism may also experience physical and psychiatric concerns (Kearney, 2016). Schwartz and colleagues (2009) found that youth who missed 12% of school time throughout the academic year exhibited poor physical health, negative thinking, and diminished self-efficacy. School absenteeism is also a primary predictor for school dropout (Ingul et al., 2012). Calderon and colleagues (2009) found that missing more than 7 days of school throughout 2 academic years predicted school dropout.

Unaddressed school absenteeism may result in several social, economic, and health-related problems into adulthood as well. Long-term effects include occupational difficulties and economic deprivation. Hibbett and colleagues (1990) found a history of school absenteeism to be a predictor of more severe employment difficulties such as an unstable job history, a shorter mean length of jobs, and a higher total number of jobs than those experienced by former non-absentee youth. Formerly absentee youth also experienced more unemployment, held lower status occupations, and reported lower family incomes than former non-absentee youth. The US Census Bureau (2012) reported

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that average salaries of youth that drop out of high school are only 66.1% of salaries of youth that graduate from high school. Employment rates for youth aged 20-24 years that dropped out of high school are also significantly lower (48%) than for youth that graduated high school (64%) (US Department of Labor, 2012). Other long-term effects include social maladjustment, marital and family conflict, and psychiatric and physical health problems (Dube & Orpinas, 2009; Hibbet & Fogelman, 1990; Kearney, 2006a; Kearney & Bates, 2005; Lounsbury, Steel, Loveland, & Gibson 2004).

Risk Factors

Research suggests a complex etiologic pathway for school absenteeism (King, Ollendick, & Tonge, 1995; King, Tonge, Heyne, & Ollendick, 2000). Common risk factors for school absenteeism are thus reviewed in detail below. Youth- and academic-related risk factors are emphasized to remain consistent with the present study. Supplementary parent, family, peer, and community risk factors are also provided.

Age. Youth of all ages may exhibit difficulties attending school. Most youth with school absenteeism, however, are aged 10-13 years (Kearney & Albano, 2007). Hansen and colleagues (1998) reported that 12.2 years was the mean age at assessment among 76 clinic-referred youth with school absenteeism. McShane and others (2001) found that the mean age of onset of school absenteeism among 192 clinic-referred youth was 12.3 years. Among 222 clinic-referred youth with school absenteeism, Kearney (2007) revealed that the mean age at assessment (not onset) was 11.7 years. Carless and colleagues (2015) found, among 60 clinic-referred youth with school absenteeism, that the mean age at assessment was 13.7 years.

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School absenteeism is also likely to occur at ages 5-6 years and 14-15 years (Kearney & Albano, 2007; Ollendick & Mayer, 1984). For example, Last and Strauss (1990) demonstrated that the peak age range for referral for school absenteeism was 13-15 years among 63 clinic-referred youth. McShane and others (2001) found that the mean age at assessment among 192 clinic-referred youth with school absenteeism was 14.2 years. Haight and colleagues (2011) reported that 14.0 years was the mean age at assessment in a community sample of youth with school absenteeism. Walter and others (2010) found that the mean age at assessment among 147 clinic-referred youth with school absenteeism was 15.1 years.

The severity of a youth's school absences often worsens with age (Hansen et al., 1998; Kleine, 1994). Youth who pursue a secondary education past the typical high school age may be at a greater risk for dropping out of school than their peers (NCES, 2011). The national event dropout rate was higher among youth aged 20-24 years (19.1%) than those aged 15-16 years (2.8%) and 17 years (2.5%) during the 2009-10 academic year. The national event dropout rate is an estimate of the percentage of both private and public high school students who left high school between the beginning of one school year and the beginning of the next without earning a high school diploma or an alternative credential such as a General Education Diploma (GED).

The present study partly aimed to evaluate the relevance of age as a risk factor for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed). Youth may exhibit school absences at any age (Kearney, 2001; Kearney, 2008b; Kearney, 2016). Previous studies, however, demonstrate that the severity of a youth's school absenteeism increases with age (Hansen et al., 1998; Kleine,

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1994; NCES, 2011). Age may be revealed as a more relevant predictor for youth with a more severe level of school absenteeism (15% of full school days missed) and a less relevant predictor for youth with less severe school absenteeism (1% and 10% of full school days missed).

Gender. Male and female youth are equally likely to exhibit school absenteeism throughout their academic career (Kearney, 2001; Kearney, 2008b; Kearney & Bates, 2005; Last, Strauss, & Francis, 1987b). For example, Kearney and Silverman (1996) evaluated 64 youth with school absenteeism that were 59.4% male. Hansen and others (1998) found that 47% of 76 clinic-referred youth with school absenteeism were male. Most studies, however, report samples that are 50%-55% male (Bernstein & Borchardt, 1996; Bernstein & Garfinkel, 1986; Egger et al., 2003; Granell de Aldaz, Feldman, Vivas, & Gelfand, 1987; Havik, Bru, & Ertesvåg, 2015; Haight, Kearney, Hendron & Schafer, 2011; Hughes, Gullone, Dudley, & Tonge, 2009; Ingul et al., 2012; McShane, Walter, & Rey, 2001; Walter et al., 2010).

Gender differences exist with respect to severity of school absenteeism. Males tend to exhibit higher rates of school nonattendance than females (Corville-Smith, Ryan, Adams, & Dalicandro, 1998; McCoy, Darmody, Smyth, & Dunne, 2007; Wagner, Dunkake, & Weiss, 2004). For example, males have a higher national status dropout rate (7.2%) than females (5.2%) (NCES, 2016b). The national status dropout rate is the percentage of 16-24 year olds who are not enrolled in school and have not earned a high school credential (either a diploma or an equivalency credential such as a GED). The motive behind a youth's school absenteeism may also differ with respect to gender. Males often miss school due to interpersonal conflicts among peers and school personnel,

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whereas females generally depart from school without misbehavior (Hansen et al., 1998; Kearney, 2001; Kelly, 1993; Last & Strauss, 1990; Morris, Finkelstein, & Fisher, 1976).

The present study partly aimed to examine gender as a relevant risk factor for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed). Male and female youth are equally likely to miss school (Kearney, 2001; Kearney, 2008b; Kearney, 2016). Extant research, however, suggests that males exhibit more severe school absenteeism than females (Corville-Smith, Ryan, Adams, & Dalicandro, 1998; McCoy, Darmody, Smyth, & Dunne, 2007; NCES, 2016b; Wagner, Dunkake, & Weiss, 2004). Gender may be revealed as a more relevant predictor for youth with a more severe level of school absenteeism (15% of full school days missed) and a less relevant predictor for youth with less severe school absenteeism (1% and 10% of full school days missed).

Ethnicity. The presence of school absenteeism tends to be higher among White youth in clinical settings than ethnic minority youth (Kearney, 2001). For example, Bernstein and Borchardt (1996) found that 46 clinic-referred youth with school absenteeism were primarily White (87%) but also African American (11%) and Hispanic (2%). Bernstein and others (1997) found 134 clinic-referred youth with school absenteeism to be primarily White (95.5%) and less so African American (1.5%), Hispanic (1.5%), and Asian (1.5%). Hansen and colleagues (1998) reported that most of their 76 clinic-referred youth with school absenteeism were White (90%), though some were African American (6%) and Hispanic (4%). Kearney (2007) reported that a majority of 222 clinic-referred youth with school absenteeism were White (67.6%), though some were Hispanic (5.4%) and African American (3.2%).

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Absenteeism rates tend to be higher among ethnic minority youth in community settings (Kearney, 2001; Kearney, 2006b). For example, Haight and others (2011) reported that a majority of community youth with school absenteeism were Hispanic (60.6%) and less so White (11.6%) or African American (10.2%). Burton and others (2014) found their longitudinal sample of 108 youth with school absenteeism to be composed of predominantly African American youth (59%). Skedgell and Kearney (2016) found that community youth with school absenteeism were predominantly Hispanic (73.5%) but also African American (10.2%), Biracial (4.3%), Asian American (3.4%), and White (2.6%). The percentage of youth exhibiting 3 or more days absent from school in a 1-month time period is highest for Native American/Alaskan Native youth (29%-34%), Hispanic youth (21%-24%), and African American youth (22%-23%) than White youth (18%-23%) (Centers for Disease Control and Prevention, 2006).

The national event dropout rate was highest for Hispanic youth (5.8%) and African American youth (4.8%), followed by White youth (2.4%) during the 2009-10 academic year (NCES, 2011). Ethnic minority trends in the event dropout rate are also present in the status dropout rate. The national status dropout rate was highest for Hispanic youth (10.6%) and African American youth (7.4%) than White youth (5.2%) during the 2014-15 academic year (NCES, 2016b).

The present study partly aimed to investigate the relevance of ethnicity as a risk factor for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed). School absenteeism tends to be more severe among White youth in clinical settings (Bernstein & Borchardt, 1996; Bernstein et al., 1997; Hansen et al., 1998; Kearney, 2007). Community settings such as the present study,

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however, demonstrate higher rates of school nonattendance among ethnic minority youth (Haight et al., 2011; Kearney, 2001; Kearney, 2006b; Kearney, 2016; NCES, 2011; NCES, 2016b). Ethnicity may be revealed as a more relevant predictor for youth with a more severe level of school absenteeism (15% of full school days missed) and a less relevant predictor for youth with less severe school absenteeism (1% and 10% of full school days missed).

Grade Level. School absenteeism may also be associated with a youth's grade level (Kearney, 2016). Youth are at greater risk for school absenteeism during their first year attending a new school such as kindergarten (Elliot, 1999; King & Bernstein, 2001; Kearney & Albano, 2000; King et al., 2001). A study of public schools in Chicago revealed that approximately 20% of youth in kindergarten were chronically absent during the 2011-2012 academic year (Ehrlich et al., 2014). As youth progress throughout elementary school, however, rates of absenteeism decrease with the lowest rates occurring in third and fourth grade (Balfanz & Byrnes, 2012).

The transition into secondary school is likely to result in school absenteeism with peaks during sixth through eighth grade (Balfanz & Byrnes, 2012; King & Bernstein, 2001). Balfanz and colleagues (2007) conducted an 8-year longitudinal study of more than 12,000 middle school youth. Approximately 15% of sixth grade youth missed at least 36 days of school during the baseline academic year. Final results revealed that absenteeism in sixth grade was a significant predictor of high school dropout. Approximately 13% of sixth grade youth with school absenteeism earned their high school diploma within the expected 8-year time frame.

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The severity of a youth's school absenteeism may worsen as he or she progresses though secondary school, often reaching its highest rate in 12th grade (Balfanz & Byrnes, 2012).Youth in high school exhibit the highest rates of chronic absenteeism (18.7%), followed by middle school youth (11.7%) and elementary school youth (10.1%) (NCES, 2016a). A Utah study also revealed that high school youth with chronic absenteeism are 7.4 times more likely to drop out of school than youth with regular school attendance (Utah Education Policy Center, 2012).

The present study partly aimed to evaluate grade level as a relevant risk factor for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed). Youth may exhibit school absences at any time throughout their academic career (Kearney, 2001; Kearney, 2008b; Kearney, 2016). Previous studies, however, demonstrate the severity of a youth's school absenteeism worsens as he or she progresses through secondary school (Balfanz & Byrnes, 2012; NCES, 2016a; Utah Education Policy Center, 2012). Grade level may be revealed as a more relevant predictor for youth with a more severe level of school absenteeism (15% of full school days missed) and a less relevant predictor for youth with less severe school absenteeism (1% and 10% of full school days missed).

Academic Achievement. School absenteeism is closely related to a youth's academic achievement (Kearney, 2016). Specifically, rates of school nonattendance may be linked to high academic potential (Goldberg, 1953; Rodriguez, Rodriguez, & Eisenberg, 1959). Sälzer and colleagues (2012) examined classroom "demand" characteristics among seventh, eighth, and ninth grade youth to determine the relationship between school absenteeism and being under-challenged at school. Youth were more

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likely to miss school if they perceived school achievement standards to be low. Youth were also more likely to be absent if they felt they had a low academic work load.

School absenteeism is more commonly associated with lower academic achievement, however (Dreyfoos, 1990; Finn, 1993; Gottfried, 2009; Lehr, Sinclair, & Christenson, 2004; Steward, Steward, Blair, Jo, & Hill, 2008). Summers and Wolfe (1977) examined sixth grade youth in Philadelphia during the 1970-71 academic year and found a negative relationship between school absenteeism and standardized test performance. Naylor and colleagues (1994) determined that psychiatric youth with school absenteeism demonstrated lower math, reading, and written language scores as well as poorer verbal comprehension skills than psychiatric controls. Research by the National Assessment of Educational Progress (NAEP) continues to demonstrate a negative relationship between school absenteeism and academic achievement. Youth who missed 3 or more days of school had lower average NAEP scores in reading and math than youth with fewer absences (Ginsburg, Jordan, & Chang, 2014). Specifically, absentee youth in fourth grade scored an average of 12 points lower on the reading assessment than youth with no absences. This equates to an entire grade level. Proficiency rates were also lower for youth who missed more school. Approximately 28% of fourth grade absentee youth scored proficient or better, whereas 38% of fourth grade youth with no absences did so.

The severity of a youth's school absences may also associated with poorer academic performance (Carver, 1970). Monk and Ibrahim (1984) examined the pattern and gross quantity of school absenteeism over one academic year and found that greater number of school absences was related to poorer performance on standardized testing among ninth grade youth. Gottfried (2014) investigated school absenteeism among

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kindergarten youth at two levels: "moderate" (11-19 school days missed) and "strong" (20+ school days missed). Youth with "moderate" school absenteeism tended to perform worse on math and reading tests than youth with fewer absences, whereas youth with "strong" school absenteeism demonstrated worse achievement than all youth across the two testing subjects.

The present study partly aimed to examine the relevance of letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), GPA, and whether or not a youth was eligible to receive an IEP during the 2015-16 academic year as risk factors for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed). Extant literature demonstrates that the severity of school absenteeism is associated with lower academic performance (Carver, 1970; Gottfried, 2014; Mark & Ibrahim, 1984). Letter grades for specific academic courses, GPA, and IEP eligibility may be revealed as more relevant predictors for youth with a more severe level of school absenteeism (15% of full school days missed) and less relevant predictors for youth with less severe school absenteeism (1% and 10% of full school days missed).

Extracurricular Participation. Rates of school absenteeism may also be associated with whether or not a youth participates in extracurricular activities. McCallum (1986) evaluated the relationship between participation in interscholastic and co-curricular activities and school absenteeism among middle school youth. Participation in activities was categorized at three levels based on time required for each activity: "no participation," "low to moderate participation," and "extensive participation." Youth

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participation in interscholastic activities correlated negatively with the number of days absent, such that youth categorized as “extensive participation” and “low to moderate participation” exhibited fewer absences than youth categorized as “no participation.” In addition, youth categorized as “extensive participation” exhibited fewer absences than youth categorized as “no participation.”

Whitley (1999) examined the relationship between participation in school sports and school absenteeism among high school youth over a 3-year period. Average number of school days missed per year was significantly lower for youth participating in school sports than youth not participating in school sports. Youth athletes missed an average of 6.52 days, whereas youth non-athletes missed an average of 12.57 days. Plavcan (2004) explored whether participation in school activities outside of the classroom improved attendance among four youth exhibiting school absenteeism. Youth were required to complete a daily school-related job for an 8-week period under the supervision of a teacher who would provide positive feedback upon completion. Attendance rates increased 14%-23% among the four youth during the intervention phase. These findings may reflect feelings of belongingness facilitated by participation in school- and non-school-related extracurricular activities. Youth with school absenteeism, however, are often disengaged from school and report feeling less popular, having friends that are viewed as less popular, and having a smaller network of friends (Angelo, 2012; Claes & Simard, 1992; Kupersmidt & Coie, 1990).

The present study partly aimed to investigate participation in extracurricular activities, specifically school sports, as a relevant predictor for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days

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missed). Youth that participate in extracurricular activities such as school sports may miss school due to games and competitions. School absenteeism tends to be less severe for these youth, however, compared to youth not involved in extracurricular activities (McCallum, 1986; Plavcan, 2004; Whitney, 1999). School sports participation may be revealed as a less relevant predictor for youth with a more severe level of school absenteeism (15% of full school days missed) and a more relevant predictor for youth with less severe school absenteeism (1% and 10% of full school days missed).

Supplementary. School absenteeism may also be influenced by many other contextual factors (Table 2). Common risk factors involve low parental involvement (Dalziel & Henthorne, 2005) and family conflict (McShane et al., 2001). Peer-related risk factors often include affiliation with an aggressive peer group (Farmer et al., 2003) and friends that have already dropped out (Claes & Simard, 1992). Community-related risk factors involve unsafe neighborhoods and a lack of available support services (De Witte, Cabus, Thyssen, Groot, & van den Brink, 2013). The present study was only able to access variables monitored by the school district and thus does not necessarily represent a comprehensive analysis of all risk factors.

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Table 2

Key Contextual Factors Related to Problematic School Absenteeism

Context	Factors
Child	Extensive work hours outside of school; Externalizing symptoms/psychopathology; Grade retention; History of absenteeism; Internalizing symptoms/psychopathology; Learning-based reinforcers of absenteeism/functions; Low self-esteem and school commitment; Persona traits and attributional styles; Poor health or academic proficiency Pregnancy; Problematic relationships with authority figures; Race and age; Trauma; Underdeveloped social and academic skills
Parent	Inadequate parenting skills; Low expectations of school performance/attendance; Maltreatment; Problematic parenting styles (permissive, authoritarian); Poor communication with school officials; Poor involvement and supervision; Psychopathology; School dropout in parents and among relatives; School withdrawal; Single parent
Family	Enmeshment; Ethnic differences from school personnel; Homelessness; Intense conflict and chaos; Large family size; Poor access to educational aids; Poor cohesion and expressiveness; Poverty; Resistance to acculturation; Stressful family transitions (e.g., divorce, illness, unemployment, moving); Transportation problems
Peer	Participation in gangs and gang-related activity; Poor participation in extracurricular activities; Pressure to conform to group demands for absenteeism or other delinquent acts; Proximity to deviant peers; Support alluring activities outside of school such as drug use; Victimization from bullies or otherwise
School	Dangerousness/poor school climate; Frequent teacher absences; High systemic levels of grade retention; Highly punitive or legal means to address all cases of problematic absenteeism; Inadequate, irrelevant, or tedious curricula; Inadequate praise for student achievement and attendance; Inadequate responsiveness to diversity issues; Inconsistent or minimal consequences for absenteeism; Poor monitoring of attendance; Poor student-teacher relationships; School-based racism and discrimination
Community	Disorganized/unsafe neighborhood; Economic pull factors (e.g., plentiful well-paying jobs requiring little formal education); Geographical cultural and subcultural values; High gang-related activity; Intense interracial tension; Lack of social and educational support services; School district policies and legal statutes regarding absenteeism

Note. Descriptive note. Adapted from "Managing school absenteeism as multiple tiers: An evidence-based and practical guide for professions" by C. A. Kearney, 2016, New York: Oxford University Press. Copyright 2016 by the Oxford University Press. Adapted with permission.

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Classification Models

Researchers have attempted to classify school absenteeism but little consensus has emerged on the most effective way to organize this population. Significant barriers to developing a successful taxonomy involve diverse terminologies and diagnostic categories as well as numerous risk factors. Major classification models such as historical, empirical, diagnostic, functional, and contemporary systems are detailed next.

Historical. Partridge (1939) proposed five different subtypes of school absenteeism: undisciplined, hysterical, desiderative, rebellious, and psychoneurotic. Key features of the first four subtypes include a lack of discipline, running away from hard situations, a desire for something, and oppositional behavior toward authoritarian parents, respectively (Kearney, 2001). The fifth subtype, psychoneurotic, referred to youth who demonstrated timidity, guilt, anxiety, tantrums, aggression, and desires for attention within an overprotective youth-parent relationship (Partridge, 1939). These distinctions guided the separation of the study of problematic school absenteeism into two camps: (1) a "traditional" camp that viewed the problem as illegal, delinquent behavior (referred to as truancy) and (2) a "contemporary" camp that viewed school absenteeism as a more complex neurotic condition (referred to as school refusal) (Kearney, 2001). The formation of this truancy-school refusal dichotomy sparked an interest in the construct of fear as a way to further classify school absenteeism.

Coolidge and colleagues (1957) outlined two groups of school absenteeism based on commonly endorsed symptomatology: characterological and neurotic. The characterological type represented the original concept of school refusal, while the neurotic type represented the original concept of school phobia (Kearney, 2001). Youth

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of the characterological type were generally older, experienced a gradual onset, and displayed more serious antisocial behaviors (Kearney & Silverman, 1993). Youth of the neurotic type were generally younger, experienced a sudden onset, and were highly anxious and fearful of separating from familiar surroundings. Considerable overlap among these distinctions led to the development of other school absenteeism taxonomies that highlighted overt youth behaviors.

Kennedy (1965; 1971) also outlined two subtypes of school absenteeism: Type I and Type II. Type I was characterized by rapid onset of the problem and no prior history of similar problems. Additional Type I features involved low grades, concerns about death, good parental relations, and questionable maternal physical health (Kennedy, 1971). Type II was characterized by gradual onset over months or years and a history of poor adjustment. Other Type II traits encompassed good grades, no concerns about death, poor parental relations, and irrelevance of maternal physical health (Kennedy, 1971). Considerable overlap, however, again existed among the subtypes. Common symptoms included fears, somatic complaints, separation anxiety, and parent-school official conflict (Kennedy, 1965).

A major criticism of early classification systems is their impractical utility. Researchers and school administrators had difficulty developing assessment and treatment methods due to overlapping symptomatology among subtypes. Historical approaches also lack a clear definition of problematic school absenteeism. The present study aimed to offer clarity to these approaches by relying on an objective measure of problematic school absenteeism (i.e., percentage of full school days missed) to inform multi-tiered assessment and intervention strategies.

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Empirical. Achenbach and Edelbrock (1978) empirically classified youth behavior into two broad-band factors: under-controlled (externalizing disorders) and over-controlled (internalizing disorders). Under-controlled behaviors involved aggression, fighting, and stealing, whereas over-controlled behaviors encompassed fear, anxiety, and depressive symptoms. Young and colleagues (1990) expanded upon this distinction to define "externalizing truant disorders" and "internalizing school refusal disorders." Behaviors characteristic of externalizing truant disorders included impulsivity, noncompliance, and other symptoms of conduct disorder or delinquency (Young, Brasic, Kisnadwala, & Leven, 1990). Internalizing school refusal disorder behaviors referred to fears, phobia, anxiety, withdrawal, fatigue, depression, and somatic complaints (Kearney, 2002). A major criticism, however, is that additional research yielded a separate school avoidance factor from the proposed externalizing and internalizing distinction (Lambert, Wiesz, & Thesiger, 1989).

Diagnostic. Bernstein and Garfinkel (1986, 1988) classified youth with school absenteeism into four subgroups based on Diagnostic Statistical Manual of Mental Disorders (DSM) categories: (1) anxiety disorder only, (2) affective disorder only, (3) anxiety and affective disorder, and (4) no anxiety or affective disorder. Some support for these distinctions has been shown (Last, Francis, Hersen, Kazdin, & Strauss, 1987a). The *DSM-5* (5th ed; DSM-5; APA, 2013), however, provides no formal diagnosis of school absenteeism. School absenteeism is incorporated as a symptom of separation anxiety (i.e., "persistent reluctance or refusal to go to school") and conduct (i.e., "often truant from school") disorder (APA, 2013, pp. 191, 470). An advantage of diagnostic classifications of school absenteeism is the facilitation of information gathering regarding symptoms,

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course, treatment options, and outcomes (Marcella & Miltenberger, 1996). A major criticism, however, is that diagnoses related to school absenteeism tend to deemphasize non-anxiety-related symptoms and behaviors (Kearney & Silverman, 1996).

Functional. Kearney and Silverman (1996) suggested a functional taxonomy of school absenteeism. A functional approach utilizes categorical and dimensional aspects to help identify the primary maintaining variables of a youth's school refusal behavior. The primary maintaining variables within the functional model involve negative and positive reinforcement: (1) avoidance of stimuli that evokes negative affect and/or positively reinforced, (2) escape of social evaluative situations, (3) pursuit of caregiver attention and reassurance, and (4) pursuit of tangible rewards outside of school. The four functions of school refusal behavior are outlined next.

Negative Reinforcement. Negative reinforcement refers to increasing the frequency of a behavior by terminating an aversive event (Kearney, 2001). Two negative reinforcement functions may contribute to school absenteeism. The first function includes youth who refuse school to avoid stimuli that evokes negative affect. Examples of key stimuli include school administration and staff, peers, buses, cafeterias, classrooms, and transitions between classes (Kearney, 2006a). Some youth may not be able to identify specific fear-related stimuli and instead report feelings of general "malaise" or "misery" while at school and may wish to pursue homeschooling (Kearney, 2001). The second function includes youth who refuse school to escape aversive social or evaluative situations. Examples of social or evaluative situations at school include conversing or interacting with peers or performing before teachers and classmates during presentations (Kearney, 2006a).

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Positive Reinforcement. School refusal behavior may also be maintained through positive reinforcement via intangible or tangible rewards (Kearney, 2001). Intangible rewards may include caregiver attention and reassurance, whereas tangible rewards may include sleeping late and watching television, among other activities (Dube & Orpinas, 2009; Kearney & Albano, 2004). Two positive reinforcement functions may contribute to problematic absenteeism. The first function includes youth who refuse school to purse intangible rewards from significant others. These youth often engage in various morning misbehaviors such as temper tantrums, refusal to get out of bed, and running away from family members, among others (Kearney & Albano, 2004). The second function includes youth who refuse school to pursue tangible rewards outside of school. Youth of this function are often tardy and skip specific classes, whole sections of the day (e.g., an afternoon), or the entire day to pursue outside reinforcement such as sleeping, watching television, spending time with friends, and engaging in drug or alcohol use, among others (Kearney, 2001). A functional classification of school absenteeism provides prescriptive remediation that addresses the motivating factors behind a youth's absences. Major criticisms of the functional approach, however, include the absence of a clear definition of problematic school absenteeism and restricted strategies since the model is tailored primarily for Tier 2.

Contemporary. Present day models of school absenteeism include two approaches. The first approach focuses on identifying predictive factors for school absenteeism by employing statistical methods (Kearney, 2016). Studies generated from this approach have been helpful in providing operational definitions of school absenteeism such as number of days missed (Cabus & De Witte, 2015) as well as

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highlighting the warning signs of school absenteeism (Ingul et al., 2012; McShane et al., 2001). These strategies do not directly inform assessment and treatment methods, however (Kearney, 2016).

The second approach involves more comprehensive strategies that account for contextual variables that influence school absenteeism. Reid (2003) proposed a preventative model for school absenteeism that emphasizes a positive school climate referred to as the Primary-Secondary Color Coded Scheme (PSCC). Youth are categorized into four risk groups based on attendance rates: 1) no risk, 2) some risk (e.g., history of school absenteeism in the family), 3) minor attendance problems, and 4) persistent attendance problems. School-based teams composed of teachers and administrators are assigned to address youth in each attendance category. PSCC is a long-term approach that addresses youth absenteeism by implementing monitoring and school-change strategies over a five-year period (Reid, 2003). A major criticism of the PSCC model, however, is a lack of clarity and utility for concretely defining problematic school absenteeism.

Lyon and Cotler (2009) expanded upon ecological theory to develop a multisystemic classification for school absenteeism. The model considers sustaining factors across youth, family, peer, and school domains while applying microsystem, mesosystem, and exosystem strategies. Microsystem strategies focus solely on the absentee youth and their family and include individual and family therapy, social skills training, and peer mentoring. Mesosystem strategies emphasize the connections between various microsystems (e.g., home and school) and include increasing contact between parents and school personnel. Exosystem strategies emphasize broad initiatives to

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indirectly alleviate school absenteeism and district-wide attendance policies. Similar to earlier models, the multisystemic approach does not provide a clear definition of problematic school absenteeism to guide assessment and intervention strategies.

Kearney (2008b) proposed an interdisciplinary and multi-tiered model for school absenteeism that focused on five levels of contextual factors: youth, parent, family, school, and community. The number of contextual factors increases as a youth’s school absenteeism becomes more severe. Problematic school absenteeism was defined as those youth who missed more than 25% of school time during the past 2 weeks, experienced severe difficulty attending classes for at least 2 weeks with significant interference in the family’s daily routine, or had more than 10 days absent during any 15 week-period in the school year. Multiaxial assessment and treatment strategies were thus designed to address the complexity of any given case of absenteeism. For example, youth may initially be asked a list of key assessment questions and then later provided specific interventions that align with the contextual factors at the primary, secondary, tertiary, quaternary, and quinary levels. A major criticism, however, is a lack of preventative strategies as school absences are only addressed after it has been determined problematic.

Models of school absenteeism have become increasingly comprehensive. A major drawback of most of these models, however, is that they remain abstract and are not easily adapted to school district procedures (Kearney & Bates, 2005; Lyon & Cotler, 2009; Pelligrini, 2007). MTSS is a multi-tiered model of solving school-related problems such as school absenteeism that addresses these limitations by hierarchically aligning specific assessment and treatment strategies with school policies (Kearney, 2016). The present study aimed to inform MTSS by determining the best way to define problematic

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school absenteeism and concretely distinguish Tier 1 and Tier 2. The present study also aimed to determine useful targets of assessment for problematic school absenteeism.

The present study investigated numerous youth- and academic-related risk factors to accomplish the aforementioned goals. Various statistical approaches have been utilized to evaluate risk factors related to school absenteeism. The majority of researchers have employed traditional parametric approaches such as logistic regression and analyses of variance (ANOVA). The implementation of non-parametric approaches is scarce but gaining favor, specifically Binary Recursive Partitioning (BRP), due to several advantages over conventional techniques. The present study was the first to employ BRP to determine the most relevant risk factors of school absenteeism in a large and highly heterogeneous community sample of youth. An overview of BRP, previous studies that have applied this technique, and the advantages and disadvantages over parametric approaches are described next.

Binary Recursive Partitioning

BRP is a non-parametric decision tree method that predicts a dependent variable based on values of various risk factors (Merkle & Shaffer, 2011). BRP utilizes an algorithm to create classes of participants with similar outcomes on a dependent variable by repeatedly splitting the sample into small, homogenous groups (Markham, Young, & Doran, 2013). The underlying algorithm encompasses three crucial parts: 1) partitioning, 2) binary, and 3) recursive (Merkle & Shaffer, 2011). "Partitioning" refers to the fact that the algorithm predicts the dependent variable by dividing the data into subgroups based on the disparate risk factors. The risk factor that results in the most homogeneous subgroups will determine the split. "Binary" describes the fact that, at any step, the

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algorithm partitions the data into only two subgroups that differ the most with respect to the dependent variable. “Recursive” refers to the fact that, within subgroups, the algorithm continues to partition the data based on other risk factors or additional splits of the same factor until a stopping criterion has been met. This procedure enables researchers to discern mutually exclusive and exhaustive subgroups of a sample that are most related to the dependent variable. The present study employed BRP techniques to predict problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed) based on values of youth- and academic-related risk factors.

Traditional approaches account for independent, linearly-additive effects when deciding the saliency of risk factors. BRP, on the other hand, considers interaction effects when deciding which risk factor results in the best split. This framework is particularly advantageous for finding multiple pathways to a specific outcome (such as problematic school absenteeism) (Markham et al., 2013). The product of BRP also mirrors the structure of Diagnostic Statistical Manual decision tree (e.g., Morgan, Olson, Krueger, Schellenberg, & Jackson, 2000) by producing “IF-THEN-ELSE” rules. BRP results are thus easy to comprehend by policy and decision makers (e.g., school officials) who may lack a more thorough understanding of multivariate statistics (Breiman, 2001). Many BRP techniques have been established. One of the most common procedures, Classification and Regression Trees (CART) analyses, is explored in detail next.

Classification and Regression Tree (CART) Analyses. CART, a form of BRP, is a “nonparametric statistical procedure that identifies mutually exclusive and exhaustive subgroups of a population whose members share common characteristics that influence

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the dependent variable" (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003, p. 173). For example, CART has been utilized to determine subgroups of men in the military who seek treatment for posttraumatic stress disorder (PTSD) based on the interaction of multiple risk factors (Fikretoglu, Brunet, Schmitz, Guay, & Pedlar, 2006). CART has also been utilized to isolate groups of individuals at the highest risk for harmful alcohol use across various risk factors (McKenzie et al., 2006). The present study utilized CART to determine subgroups of youth at the highest risk for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed) based on multiple youth- and academic-related risk factors.

CART analyses produce two types of trees: 1) classification and 2) regression. "Classification" trees contain categorical dependent variables, while "regression" trees contain continuous dependent variables (Merkle & Shaffer, 2011). The output of these two CART analyses is a multilevel diagram where the various splits on risk factors resemble the branches of a tree (Lemon et al., 2003). Steps of the tree-building process are outlined below. The output of a CART analyses by Fikretoglu and colleagues (2006) will be referenced throughout as an example of a classification tree (Figure 3).

Prior Probabilities. CART allows researchers to specify probabilities of group membership for the categorical dependent variable prior to beginning the tree-growing process. Prior probabilities are estimates of the overall relative frequency for each category of the dependent variable without any knowledge of the values of the risk factors. Prior probabilities thus helps to correct any tree growth caused by data in the sample that is not representative of the entire population. Three types of prior probabilities may be employed: 1) equal, 2) empirical, or 3) custom. Equal probabilities

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Figure 3. Example of CART analysis. Reprinted from "Posttraumatic stress disorder and treatment seeking in a nationally representative Canadian military sample" by D. Fikretoglu, A. Brunet, N. Schmitz, S. Guay, & D. Pedlar, 2006, *Journal of Traumatic Stress, 19(6),* p. 855. Copyright 2006 by International Society of Traumatic Stress Studies. Reprinted with permission. MDD = major depressive disorder, Support = social support

are utilized when an equal distribution of class membership for the independent variable is observed in the population. For example, if a binary dependent variable results in 50% of the participants in each category. Empirical priors, the type of probabilities employed in the present study, are obtained from the sample and utilized when the distribution of

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class membership for the independent variable is representative of the population distribution. Custom probabilities are utilized when the researcher wants to manually specify proportions, percentages, frequency counts, or any other values that represent the distribution of class membership for the dependent variable.

Nodes and Splitting. Nodes in the tree are represented by either circles or rectangles, depending on where the node is located in the tree building process. Nodes contain a group of participants from the sample. CART trees begin with one “node” that contains all of the participants in the sample, which is referred to as the parent node (Lemon et al., 2003) (note Figure 3; parent node of the categorical dependent variable of men in the military who sought or never sought treatment for PTSD). From the parent node, the CART procedure branches out into two descent nodes, referred to as child nodes (i.e., circles) (Lemon et al., 2003). These branches represent one of the risk factors and are referred to as splits (Merkle & Shaffer, 2011). The initial split from the parent node results in two subgroups of the sample that differ most with respect to the dependent variable (Lemon et al., 2003) (see Figure 3; first split on PTSD interference symptom score). The tree-growing methodology continues within each of the two child nodes by evaluating each of the risk factors to select the one that results in the next most significant split, according to some predetermined splitting criterion (described later) (Lemon et al., 2003).

The splitting procedure continues in this way until a stopping criterion (also defined later) is reached. Once a stopping criterion has been reached, mutually exclusive and exhaustive subgroups of the sample will remain. These homogenous subgroups are referred to as terminal nodes (i.e., rectangles) (Lemon et al., 2003). CART thus enables

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researchers to discern distinct clusters of a sample that are most related to the dependent variable based on common risk factors (i.e., Figure 3; common risk factors most related to the dependent variable (treatment seeking) include PTSD interference symptom score, occurrence of lifetime trauma, spirituality, social support, major depressive disorder, and gender).

In a classification tree, which is the type of analysis that was employed in this study, the probability of having the categorical dependent variable is estimated among those participants within each node (i.e., Figure 3; probability of seeking treatment based solely on a PTSD interference symptom score of > 3.5 = 67.1%). On the other hand, in a regression tree, the average value of the continuous dependent measure among the participants is estimated within each node (Lemon et al., 2003). The present study constructed three classification trees to determine the most relevant risk factors for problematic school absenteeism defined at three distinct cutoffs (categorical dependent variable = exhibits greater than or equal to 1%, 10%, and 15% of full school days absent or does not exhibit greater than 1%, 10%, and 15% of full school days absent). Each node will provide the probability that youth exhibited problematic school absenteeism based on various risk factors.

Splitting Criteria. Branches from the parent node to the respective child nodes represent splits in the tree growing process. The criteria for determining these splits are based on symmetrical, concave impurity functions (Lemon et al., 2003). Impurity functions may include the Gini criterion, entropy, and the minimum error. The Gini criterion, which is the impurity function employed in the present study, is most commonly utilized when the dependent variable is categorical (Breiman, Friedman,

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Olshen, & Stone, 1984). The Gini criterion works to determine the "optimal split" by finding the risk factor that best discriminates between classes of the dependent variable (**y**) (xi; where i represents a particular risk factor taking the value of 0 or 1) (Merkle & Shaffer, 2011). Splits that adequately differentiate between separate classes of **y** result in nodes that have low impurity (i.e., all 0s or 1s), whereas splits that do a bad job of differentiating between separate classes of **y** result in nodes that have high impurity (i.e., a mixture of 0s and 1s).

The Gini criterion has a minimum value of 0, which represents when the two child nodes differ the most with respect to the dependent variable (Strobl, Malley, & Tutz, 2009). The maximum value of the Gini criterion is .5. The impurity value achieved by a split is measured by subtracting the weighted average of the impurity of the two child nodes from the impurity of the parent node (Lemon et al., 2003). The risk factor that results in the largest reduction in the impurity value (i.e. Gini criterion) is selected for splitting at each step in the tree-growing process. Splitting continues recursively until some predetermined stopping criterion (reviewed next) is met.

Stopping Criteria. CART allows researchers to predetermine criteria for stopping the tree-growing process, called stopping rules *(*Lemon et al., 2003). Stopping rules define the minimum degree of statistical difference between subgroups that is considered meaningful *(*Lemon et al., 2003). The tree-growing process may be stopped in multiple ways. According to Lemon and others (2003), researchers may first define the minimum number of participants allowed in the child or terminal nodes (p. 175). Splitting will advance until the threshold for the minimum number of participants in each node has been met. Second, researchers may define the maximum number of levels to which the

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tree can grow or the maximum number of risk factors that can define a single terminal node (p. 175). Splitting will thus continue until the maximum number of factors has been reached. Third, researchers may define the minimum value of the impurity function for a splitting criterion (p. 175). Splitting will advance until the minimum reduction in the Gini criterion that can still be considered meaningful has been achieved.

CART allows all three stopping criteria to be utilized simultaneously to increase the predictive validity of the model. Even with these three methods, however, determining the stopping point for a tree can be difficult. Important associations between the risk factors and dependent variable may be missed by stopping the tree-growing process too soon. For example, the ability to predict an observed data set can always be improved by adding additional splits to the model. The stopping rules are intended to over-fit the data and build trees that fit the current data set well (Merkle & Shaffer, 2011). Yet, each additional split reduces the ability of the tree-model to predict other data sets. The optimal number of splits in a tree thus relies on a generalizability criterion (Merkle & Shaffer, 2011). Building large trees and then removing splits that do not significantly contribute to the tree's predictive validity is another approach to improving the generalizability of a tree and is discussed in more detail below.

Overfitting and Pruning. The CART procedure may sometimes adjust a tree too closely to the observed sample, referred to as overfitting (Strobl, Malley, & Tutz, 2009). Overfitting is troublesome due to the tree's tendency to subsume the random variation that is present in the data set as a result of random sampling. Non-parametric approaches such as BRP thus rely on pruning to correct for this random variation. *Pruning* can be described as a sequential deletion of uninfluential splits in a tree (Merkle

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& Shaffer, 2011). The tree pruning process occurs in two steps: 1) deciding which part of the tree to prune and 2) measuring each pruned tree's ability to predict new data. Pruning thus provides researchers with smaller trees, each with a different number of terminal nodes that are nested within the original tree.

The CART procedure will produce different trees depending on the random sampling that occurs within the population (Lemon et al., 2003). A technique commonly employed to estimate how different alternate sample trees would be is *k*-fold cross validation (Merkle & Shaffer, 2011). *K*-fold cross validation breaks the data into *k* subsets. A tree is calculated using all *k* subsets except for one, referred to as the "training" subset. The calculated tree is then applied to the training subset. The training subset becomes known as the "validation" subset and a misclassification cost, R(T), (i.e., goodness of fit) is determined for each pruned tree. Different measures of misclassification cost, R(T), have been established for selecting among the pruned trees such as minimum cost-complexity, least absolute shrinkage, selection operator, and the one standard-error (SE) rule (Lemon et al., 2003). The one SE rule, which is the misclassification cost, R(T), employed in the present study, suggests that the optimal tree is the smallest tree whose cost is within one SE of the tree with minimum misclassification cost. Results are summarized in a table to ease comprehension and selection of the optimal tree (Brieman, Friedman, Olshen, & Stone, 1984). Pruning strategies are often utilized in conjunction with the three stopping criteria in CART analyses to further increase the predictive validity of a tree.

CART in Research. Non-parametric approaches have been employed in a variety of different research disciplines. CART procedures, however, are most often applied in

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the prediction of medical- and physical-related phenomenon. For example, CART has been utilized to predict recovery rates from comas after enduring a cerebral hypoxia-ischemia (Levy et al., 1985), the need for radiographic assessment in children with upper-extremity injuries (McConnochie, Roghmann, & Pasternack, 1993), and the identification of risk factors for pre-term and small-for-gestational-age births (Zhang & Bracken, 1995). Other examples of CART in medical settings include predicting major complications in patients with acute chest pain (Goldman et al., 1996), the utilization of medical procedures such as caesarian section (Gregory, Korst, & Platt, 2001), and the assessment of risk factors for influenza treatment strategies (Smith & Roberts, 2002).

Researchers have also applied CART analyses to address concerns in clinical practice. Raymond and colleagues (1994) utilized CART to examine whether variables other than gestational age and birth weight could accurately predict pregnancy outcomes (i.e. mortality and morbidity) in infants born in Addis Ababa, Ethiopia in 1987 and 1988. Calvocoressi and colleagues (2005) utilized CART to predict adherence to mammography screening guidelines among 1,229 women aged 40-49 years or 50-79 years in Connecticut from 1996-1998. BRP techniques selected six of 22 possible risk factors to form three subgroups for women aged 40-49 years and five subgroups for women aged 50-79 years. Women aged 40-49 years who were most adherent to the mammography screening guidelines had received a health-care provider's recommendation. For women aged 50-79 years, adherence to the mammography screening guidelines included four predictors: a belief that mammograms were useful, a history of adherence, low or moderate perceived breast cancer susceptibility, and a family income of $15,000 or more (Calvocoressi, Stolar, Kasl, Claus, & Jones, 2005). Other

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examples of CART in clinical health settings include predicting long-term outcome among head trauma patients (Temkin, Holubkov, Machamer, Winn, & Dikmen, 1995) and cost-effectiveness of colorectal cancer screening technologies (McGrath, Ponich, & Gregor, 2002).

The utilization of non-parametric approaches in psychological research is notably more limited but gaining popularity. CART analyses have been utilized to assess the relationship between neuroticism, self-esteem, and depressive disorders (Schmitz, Kugler, & Rollnick, 2003) and to predict diverse routes into positive and negative affect (Gruenewald, Mroczek, Ryff, & Singer, 2008). Other examples of CART include the prediction of treatment seeking among military men (Fikretoglu et al., 2006) and the identification of subgroups of individuals at the highest risk for harmful alcohol use (McKenzie et al., 2006).

Markham and colleagues (2013) employed recursive partitioning techniques to identify subgroups of individuals at the highest risk for problematic gambling. Markham and others considered demographic (i.e., age, gender, education), social (i.e., occupation, workforce status), and cultural (i.e., residency status, indigenous status) risk factors. The researchers identified several subgroups with a high likelihood of problematic gambling based on the final tree model. The most relevant risk factors for problematic gambling included Indigenous status, who accompanied the participant to the venue, the number of electronic gambling machines at the venue, and the number of alcoholic drinks consumed at the venue. Specifically, those individuals visiting venues with a large number of electronic gambling machines that traveled alone either by taxi, bus, or walking were at the highest risk for problematic gambling. The identification of the most relevant risk

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factors yields important implications for targeted harm minimization and treatment interventions (Markham et al., 2013).

Ross and Kearney (2017) identified subgroups of youth at the highest risk for post-traumatic stress disorder (PTSD) re-experiencing, avoidance, and hyperarousal symptom clusters utilizing recursive partitioning techniques. Demographic (i.e., gender, age, ethnicity, and type of maltreatment experienced), affective (i.e., depression, ineffectiveness, anhedonia, negative self-esteem, negative mood, interpersonal problems, dissociation, dissociative amnesia, absorption and imaginative involvement, depersonalization and derealization, and passive influence) and cognitive (i.e., posttraumatic cognitions, negative cognitions about the self, negative cognitions about the world, self-blame, full scale IQ, processing speed, working memory, verbal comprehension, and perceptual reasoning) risk factors were considered. Several subgroups with a high likelihood of PTSD re-experiencing, avoidance, and hyperarousal symptoms clusters were identified based on the final tree-models. The most relevant risk factors for PTSD re-experiencing symptoms included above average levels of posttraumatic cognitions and anhedonia, greater negative mood, low average or better processing speed scores, and African American, Native American, and Biracial ethnicities. The most relevant risk factors for PTSD avoidance symptoms included higher levels of depersonalization and derealization, average or below average verbal comprehension scores, younger age, and sexual maltreatment. The most relevant risk factors for PTSD hyperarousal symptoms included higher levels of negative cognitions about the self, above average levels of dissociation, an average full scale IQ score, low or below average working memory scores, and higher levels of posttraumatic cognitions.

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The identification of the most vulnerable subgroups for PTSD symptoms clusters affords important implications for targeted assessment and treatment (Ross & Kearney, 2015).

CART vs. Other Multivariate Methods. Nonparametric approaches have been increasing in popularity, though more conventional methods remain dominant in psychology. A number of multivariate statistical methods are typically applied to categorize groups of participants within a larger population. These techniques include standard logistic regressions, linear modeling, and cluster analysis. These methods, however, involve notable limitations when used to discern high-risk subgroups based on numerous risk factors. The remainder of this section describes these limitations and then outlines the advantages of CART over more conventional parametric approaches within the context of the present study.

First, the present study intended to evaluate numerous ordinal and nominal risk factors simultaneously. All variables in logistic regression models, however, must be dichotomous to be entered into the analyses (Zhang & Singer, 2010). This requires the researcher to dummy code each level of each risk factor prior to entering it into the equation, which is likely inefficient for studies with a large number of factors such as the present study. Second, logistic regression models do not allow for the simultaneous consideration of multiple risk factors (Lemon et al., 2003). CART, however, is free of significance tests and proposes no stochastic model on the data. The risk factors can thus be of all types (i.e., continuous, ordinal, and categorical) and entered simultaneously with minimal change to the underlying algorithm and output (Merkle & Shaffer, 2011).

Third, given that the present study intended to investigate a number of different risk factors, multicollinearity would be a significant concern if traditional parametric

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approaches such as logistic regression were employed. For example, when highly correlated risk factors are entered into a logistic regression the statistical power of the analyses is greatly reduced. Merely altering the order in which the risk factors are entered can also impact their weights and thus the overall significance of those factors (Kiernen, Kraemer, Winkleby, King, & Taylor, 2001). In contrast, nonparametric approaches such as CART examine each risk factor only with respect to whether it provides the optimum split at each level. CART analyses are thus minimally impacted by the problems associated with multicollinearity.

Lastly, traditional approaches such as logistic regression require the investigator to make explicit decisions about which interaction effects to include within the analyses. These explicit decisions allow potential biases to emerge within the model, however. The order in which the interaction effects have to be added (e.g., lower order versus higher order) can also significantly affect the weightings of the risk factors as well as the overall statistical power of the analyses (Kiernan et al., 2001). CART, on the other hand, relaxes the notion that the same tree-model holds true for all cases within a population and allows for the development of separate regressions for each subgroup (Magidson & Vermunt, 2005). CART is thus particularly well-suited for finding multiple, differentiated routes to a particular outcome from complex datasets that may be highly dimensional (Markham et al., 2013).

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Rationale for CART Application and Purpose of the Proposed Study

Risk factors for school absenteeism in youth have been well-documented. Traditional research on risk factors often utilized parametric approaches such as logistic regression, structural equation modeling (SEM), and analysis of variance (ANOVA). However, treatment interventions developed from the findings of these traditional approaches are geared towards the typical youth with school absenteeism, without consideration of the most relevant factors for high risk subgroups of youth with problematic school absenteeism (Forthofer & Bryant, 2000).

The identification of the most relevant risk factors for problematic school absenteeism is important for several reasons. First, the progression from an occasional missed day of school into problematic school absenteeism is associated with a wide variety of risk factors. It is thus important to examine the pattern of these factors, as it may improve our understanding of the development of problematic school absenteeism in youth (Walter et al., 2013). Second, a better appreciation of the most relevant risk factors may engender more accurate identification of highest risk subgroups of youth with problematic school absenteeism. Third, the identification of the highest risk subgroups of youth with problematic school absenteeism may assist in the development of targeted assessment strategies for school administrators and officials in charge of remediating the behavior.

The present study thus aimed to expand upon previous work by employing a nonparametric approach (i.e., BRP techniques) to determine the most relevant risk factors for problematic school absenteeism. Problematic school absenteeism was defined at three distinct cutoffs based on previous literature: 1%, 10%, and 15% of full school days

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missed (Egger et al., 2003; Ingul et al., 2012; NCES, 2016a). The present study simultaneously evaluated a variety of youth- and academic-related risk factors among a large, gender-balanced, and ethnically-diverse sample of community youth. Youth-related risk factors included age, gender, and ethnicity. Academic-related risk factors included grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), GPA, whether or not a youth was eligible to receive an IEP during the 2015-16 academic year, and whether or not a youth participated in school sports during the 2015-16 academic year. The present study aimed to inform the MTSS model by examining the amount of overlap among risk factors identified as most relevant at each distinct cutoff and determining the most appropriate way to concretely distinguish Tier 1 and Tier 2 in the model. The identified risk factors also helped determine useful methods of assessment for problematic school absenteeism.

Specific risk factors were hypothesized to emerge as more relevant for problematic school absenteeism based on the extant literature. BRP methods, however, were originally designed for exploratory analyses, rather than testing a priori hypotheses (Kiernen et al., 2001). CART procedures are thus best applied toward generating, not testing, hypotheses (Markham et al., 2013). Nevertheless, considering which risk factors to include and the direction of expected relationships between factors is an important prerequisite of conducting CART analyses (Lemon et al., 2003). Hypotheses for the present study are thus provided below.

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Hypotheses

The first hypothesis utilized CART procedures to identify the most relevant risk factors for problematic school absenteeism, defined as equal to or greater than 1% of full school days missed (Egger et al., 2003). Participation in school sports was expected to be the most relevant risk factor and produce the greatest impurity reduction within the tree-model. Specifically, youth that had participated in a school sport during the 2015-16 academic year were expected to emerge as being at high risk for 1% of full school days missed. Preliminary studies suggest that participation in extracurricular activities may be uniquely associated with less severe school absenteeism (McCallum, 1986; Plavac, 2004; Whitney, 1999).

The second hypothesis utilized CART procedures to identify the most relevant risk factors for problematic school absenteeism, defined as equal to or greater than 10% of full school days missed (NCES, 2016). Grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), and GPA were expected to be relevant risk factors and produce the greatest impurity reductions within tree-models. Specifically, youth in high school that had earned a failing grade in at least one core academic course and a lower GPA were expected to emerge as being at high risk for 10% of full school days missed. Preliminary studies suggest that grade level may also be uniquely associated with school absenteeism (Kearney, 2016). Specifically, a youth's school absenteeism often worsens as the youth progresses though secondary school (NCES, 2016a; Utah Education Policy Center, 2012). Poor academic performance may also be independently associated with school absenteeism (Ginsburg et al., 2014;

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Gottfried, 2014; Lehr et al., 2004; Steward et al., 2008). For example, youth with low academic self-concepts and learning problems in math, reading, and written language may be at a greater risk for exhibiting school absenteeism (Naylor, Staskowski, Kenney, & King, 1994; Reid, 1984).

The third hypothesis utilized CART procedures to identify the most relevant risk factors for problematic school absenteeism, defined as equal to or greater than 15% of full school days missed (Ingul et al., 2012). Age, gender and ethnicity were expected to be relevant risk factors and produce the greatest impurity reductions within tree-models. Specifically, older male Hispanic youth were expected to emerge as being at high risk for 15% of full school days missed. Preliminary studies suggest that age may be uniquely associated with more severe school absenteeism (Hansen et al., 1998; Kleine, 1994; NCES, 2011). Specifically, the severity of a youth's school absences often worsens with age. Gender may also be uniquely associated with more severe school absenteeism (APA, 2013). For example, males tend to exhibit higher rates of school nonattendance than females (Corville-Smith et al., 1998; McCoy et al., 2007; Wagner et al., 2004). Research suggests that ethnicity may be uniquely associated with more severe school absenteeism as well (APA, 2013; NCES, 2015; Virtanen, Lerkkanen, Poikkeus, & Kuorelahti, 2014). School absenteeism rates tend to be significantly higher among Hispanic youth than White or African American youth in community settings (Haight et al., 2011; Kearney, 2001; Kearney, 2006; NCES, 2015; Skedgell & Kearney, 2016).

Several post-hoc analyses were conducted given the exploratory nature of recursive partitioning techniques. For example, CART was employed at different developmental levels (i.e., elementary vs. middle vs. high school). Research indicates that childhood

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development has a significant impact on a youth's education-related outcomes such as school readiness, academic performance, school adjustment, and school absenteeism (Blair, 2002; Ladd, 1990; Martin, & Ochsner, 2016; Raver, 2003; Schonert-Reichl et al., 2015; Spodek, & Saracho, 2014; Steinberg et al., 1992). The present study thus examined whether the most relevant risk factors identified at each cut off (1%, 10%, and 15% of full school days missed) differed based on a youth's developmental level (e.g., elementary vs. middle vs. high school).

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CHAPTER 3

METHODOLOGY

Participants

Participants included 316,004 youth aged 4-21 years (M = 11.4; SD = 3.49) from the Clark County School District (CCSD) of Nevada during the 2015-16 academic year. Youth were in elementary school (n = 134,962), middle school (n = 77,799), and high school (n = 103,243). Youth were 51.4% male and 48.6% female. The sample was Hispanic (44.9%; n = 142,007), Caucasian (26.1%; n = 82,324), African-American (14.3%; n = 45,257), Asian-American (6.4%; n = 20,086), Biracial (6.3%; n = 19,902), Pacific Islander (1.6%; n = 5,081), American-Indian (0.4%; n = 1,337), and unknown (0.0%; n = 10). A mean of 6.32% (SD = 8.57) of school days missed was observed, as well as a mean GPA of 2.51. Some youth (10.3%) were eligible to receive an Individualized Education Plan (IEP).

Measures

Youth Variables. The CCSD Assessment, Accountability, Research, and School Improvement Department (AARSID) maintains an annual database of all local schools with student-related information such as grades, transcripts, and health records according to guidelines set by the US Department of Education. The following youth demographic variables were available in the database and utilized in the present study: age, gender, and ethnicity (Table 3).

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Table 3

Operational Definitions of Youth- and Academic-Related Variables

Variable	Definition
Age	Age in years based on the first day of the 2015-16 academic year
Algebra I	High school Algebra course required to graduate and typically enrolled in by 9th grade youth
Algebra II	High school Algebra course required to graduate and typically enrolled in by 11th grade youth
Biology	High school Biology course required to graduate and typically enrolled in by 9th grade youth
Chemistry	High school Chemistry course required to graduate and typically enrolled in by 10th or 11th grade youth
English 9	High school English course required to graduate and typically enrolled in by 9th grade youth
English 10	High school English course required to graduate and typically enrolled in by 10th grade youth
English 11	High school English course required to graduate and typically enrolled in by 11th grade youth
English 12	High school English course required to graduate and typically enrolled in by 12th grade youth
Gender	Self-reported gender
Ethnicity	Self-reported ethnicity
Geometry	High school Geometry course required to graduate and typically enrolled in by 10th grade youth
Grade Level	Grade level during the 2015-16 academic year
Grade Point Average (GPA)	Cumulative high school GPA categorized at five different levels: 0) unknown/nonexistent, 1) 0.00-1.00, 2) 1.01-2.00, 3) 2.01-3.00, and 4) 3.01-4.00
Individualized Education Plan (IEP)	Whether or not a youth was eligible to receive special education services during the 2015-16 academic year
Sports Participation	Whether or not a youth participated in middle or high school sports during the 2015-16 academic year

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Academic Variables. The CCSD AARSID database contained the following academic-related variables utilized in the present study: grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), GPA, whether or not a youth was eligible to receive an IEP during the 2015-16 academic year, and whether or not a youth participated in school sports during the 2015-16 academic year.

School Absenteeism. Total number of school days missed during the 2015-16 academic year was divided by the total number of school days possible for the academic year and multiplied by 100. Percentage of days absent was examined categorically at three predetermined cutoffs (1%, 10%, and 15%).

Background Procedure

The CCSD AARSID database is assembled according to guidelines set by the US Department of Education's Family Policy Compliance Office (FPCO). The FPCO is designed to meet the needs of students of all ages by effectively implementing two laws: the Family Educational Rights and Privacy Act (FERPA) and the Protection of Pupil Rights Amendment (PPRA) (US Department of Education, 2011). Both laws ensure specific student and parental rights in education.

FERPA (20 U.S.C. § 1232g; 34 CFR Part 99), the law that directly relates to this study, protects the privacy of education records for students and parents. "Education records," in this context, is defined as records that contain student-related information such as grades, transcripts, and health records, among others, that are maintained by an educational agency or by a party acting for the agency (US Department of Education,

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2011). FERPA applies to all educational agencies (e.g., school districts, postsecondary institutions) that receive funds from the US Department of Education. However, educational agencies are only required to provide privacy protections for the education records that it already maintains rather than ensure the privacy of specific records.

FERPA guarantees that parents have certain rights with respect to their child's education records. Students, referred to as "eligible students," may also obtain these rights at 18 years of age or start of attendance at a postsecondary institution. The following rights are secured by parents and eligible students through FERPA: 1) the right to inspect and review student educational records maintained by an educational agency and 2) the right to request that an educational agency correct records that are believed to be inaccurate or misleading. An educational agency has 45 days to provide a copy of a student's educational records if these rights are exercised by parents or eligible students (US Department of Education, 2011).

FERPA requires that educational agencies notify parents and eligible students annually of these rights. FERPA allows the means of notification to be at discretion of the agency. These means may include an excerpt in the student handbook or the PTA bulletin or a special letter, among others. However, the annual notification must include the following elements: 1) the parent's and eligible student's right to inspect and review a student's education records, 2) the right to seek to amend the records, 3) the right to consent to disclosure of personally identifiable information from the records, and 4) the right to file a complaint with the FCPO regarding an alleged failure by the educational agency to comply with FERPA (US Department of Education, 2011).

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FERPA ensures that an educational agency must obtain written permission from parents or eligible students to release information from a student's educational record. However, an exception to this standard centers on the disclosure of directory information (US Department of Education, 2011). "Directory information," in this context, is defined as information that would not generally be considered harmful or an invasion of privacy. Examples of such information include the student's name, address, telephone number, grade level, and dates of attendance, among others. According to FERPA, an educational agency must information parents and eligible students of any solicitations of directory information and allow a reasonable amount of time to request that the agency not disclose the information.

FERPA contains additional exceptions that allows educational agencies permission to disclose a student's education records, without consent, to the following parties (34 CFR § 99.31): 1) education officials with legitimate educational interest, 2) other educational agencies to which a student is transferring, 3) specific officials for audit purposes, 4) appropriate parties in connection with financial aid to a student, 5) organizations conducting studies for or on behalf of the educational agency, 6) accrediting organizations, 7) to comply with a judicial order, 8) officials in cases of health and safety emergencies, and 9) state or local authorities within a juvenile justice system (US Department of Education, 2011). The fifth criteria "organizations conducting studies for or on behalf of the educational agency" directly applies to this study. FERPA requires that a written agreement be constructed among the educational agency and the organization to specify the purposes of the study and the use and destruction of the information (34 CFR 99.21 (a)(6)) (US Department of Education). The present study was

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approved by both the CCSD Institutional Review Board (Protocol – 77) (Appendix A) and the University of Nevada, Las Vegas Institutional Review Board (Protocol – 852383-1) (Appendix B).

Procedure and Data Analyses

The most relevant risk factors for problematic school absenteeism were identified via CART analyses using SPSS decision tree software. CART, a form of BRP, is a nonparametric statistical procedure that enables researchers to easily identify subgroups of a diverse population that are most related to a dependent variable (school absenteeism) based on numerous risk factors. CART is preferable to conventional parametric approaches in identifying high risk subgroups due to the simultaneous consideration of multiple risk factors and greater resistance to the effects of multicollinearity, outliers, and missing data (Kiernan et al., 2001; Merkle & Shafer, 2011; Zhang & Singer, 2010). CART also has the ability to uncover nonlinear relationships by examining all higher order interactions among the risk factors (Fikretoglu et al., 2006). The present study utilized CART to identify the most relevant youth- and academic-related risk factors for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed).

Unequal distribution of group membership was observed at each of the three distinct cutoffs for problematic school absenteeism. For example, the base rate of problematic school absenteeism defined as 1% of full school days missed was 85.2% (*n* = 290,157). The base rate of problematic school absenteeism defined as 10% of full school days missed was 16.3% (*n* = 51,359). The base rate of problematic school absenteeism defined as 15% of full school days missed was 8.6% (*n* = 27,238). These sample distributions of

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problematic school absenteeism were expected to be representative of the population distribution. Empirical prior probabilities were thus obtained. Probabilities were adjusted based on misclassification costs in some tree-models to enhance predictive validity.

All youth began as a single group (parent node). The parent node was split into two groups (child nodes) by the youth- or academic-related risk factor deemed most relevant by producing the greatest impurity reduction (the risk factor that provides the greatest reduction in total variation within the dependent variable). This decision was made utilizing the Gini criterion (discussed above), which is a measure of subgroup variability (Fikretoglu et al., 2006). The Gini criterion has a minimum value of 0, which indicates that the two child nodes differ the most with respect to the dependent variable (Strobl, Malley, & Tutz, 2009). The maximum value of the Gini criterion is .5. The youth- or academic-related risk factor that produced the largest reduction in the Gini criterion was deemed most relevant and selected for the next split. Splitting continued in this way until specific stopping criteria were met.

Specific criteria for stopping the tree growing process (stopping rules) are determined a-priori by researchers. Several criteria, consistent with Lemon and colleagues' (2003), were employed as stopping rules in this study. First, if a child node became pure or all cases in a child node have identical values of the dependent variable (school absenteeism), then the node became a terminal node and was not split. Second, if all cases in a child node had identical values for each risk factor, then the tree growing process was stopped. Third, if the current tree depth reached the user-specified maximum tree depth limit value of 5, then the node became a terminal node and was not split. Fourth, if the size of a child node was less than the user-specified minimum node size

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value of 10% of the total sample (31,600 youth), then the tree growing process was stopped. Fifth, if the split of a node resulted in a child node whose node size is less than the user-specified minimum child node size value of 5% of the total sample (15,800 youth), then the node became a terminal node and was not split. Sixth, if the improvement value for the best split was less than the user-specified minimum improvement value of .0001, then the tree growing process was stopped. The aforementioned criteria are the software's default settings as well as the most conservative criteria when conducting CART analyses (Zhang & Singer, 2010). Surrogate split algorithms were utilized to automatically handle missing data (Zhang & Singer, 2010).

CART does not employ significance tests or standardized selection methods such as Akaike's information criterion when interpreting a model's salience (Merkle & Shaffer, 2011; Strobl et al., 2009). The validity of a tree-model is determined based on its predictive accuracy or ability to correctly identify highest risk subgroups when applied to different samples. The present study implemented several validation strategies to increase the accuracy and generalizability of the classification tree-models. Specifically, the present study utilized *k*-fold cross validation (Merkle & Shaffer, 2011). This process divides the total sample into *k* subsets or folds. Larger numbers of sample folds result in fewer excluded observations from each tree-model. The present study specified the standard value of 10 sample folds for each of the three tree-models. Ten tree-models were constructed by excluding data from each fold in turn. For example, the first tree is based on all observations except for those in the first sample fold, the second tree is based on all observations except for those in the second sample fold, and so on (IBM, 2011).

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A misclassification cost, R(T), is determined for each tree-model by applying the model to the excluded sample fold. The one SE rule was employed as a measure of misclassification cost, R(T), for selecting among the pruned trees. The one SE rule suggests that the optimal final tree-model is the smallest tree whose misclassification cost is within one SE of the tree with the minimum misclassification cost. The one SE rule provides the best predictive accuracy with the fewest number of risk factors (Lemon et al., 2003).

Findings from the present study are displayed as three final tree-models for school absenteeism defined as 1%, 10%, or 15% of full school days missed. Each node in the tree displays the youth- or academic-related risk factor deemed most relevant and the resulting improvement value. Each node also contains the frequency counts and percentage of youth that exhibited school absenteeism defined as 1%, 10%, of 15% of full school days missed (dependent variable). Classification and risk tables for each tree-model were also generated (IBM, 2011). Classification tables provide the number of youth classified correctly and incorrectly with respect to the dependent variable. The present study generated classification or prediction rules for each tree-model as well. Prediction rules appear as simple text and are expressed as a set of "if…then" statements that describe the tree-models predictions for each terminal node (IBM, 2011).

Risk tables provide a measure of the tree-model's overall predictive accuracy (i.e., cross-validated risk estimate) computed as the average of the misclassification costs across all pruned tree-models. Risk estimates below 0.500 indicate that a tree-model predicts the categorical dependent variable more accurately than chance, with lower values representing greater predictive accuracy (Schemper, 2003). Risk estimates near

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0.300 are most commonly reported in CART research (Kattan & Cowen, 2009). The present study thus considered cross-validated risk estimates above 0.500 as “poor,” risk estimates between 0.499 and 0.330 as “adequate,” and risk estimates of 0.329 or below as “good.”

BRP techniques were originally designed for exploratory analyses, rather than testing a priori hypotheses and are thus best applied toward generating hypotheses (Kiernan et al., 2001; Markham et al., 2013). Several findings, however, were expected based on the extant literature about risk factors for school absenteeism. Hypothesis 1 utilized CART analyses to identify youth at the highest risk for school absenteeism defined as 1% of full school days missed based on youth- and academic-related risk factors. Participation in school sports were expected to be the most relevant risk factor and produce the greatest impurity reductions within the final tree-model. Hypothesis 2 utilized CART analyses to identify youth at the highest risk for school absenteeism defined as 10% of full school days missed based on youth- and academic-related risk factors. Grade level, letter grades for specific high school core academic course (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), and GPA were expected to be relevant risk factors and produce the greatest impurity reductions within the final tree-model. Hypothesis 3 utilized CART analyses to identify youth at the highest risk for school absenteeism defined as 15% of full school days missed based on youth- and academic-related risk factors. Age, gender, and ethnicity were expected to be relevant risk factors and produce the greatest impurity reductions within the final tree-model.

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Post Hoc Analyses

Several post hoc analyses were conducted given the exploratory nature of recursive partitioning techniques. CART was employed at different developmental levels (i.e., elementary vs. middle vs. high school). Specifically, three classification tree-models were constructed for each developmental level, one to represent each of the distinct cutoffs for problematic school absenteeism (1%, 10%, and 15% of full school days missed). Each classification tree-model was constructed in the same manner as described above to identify the most relevant risk factors. The present study examined whether the most relevant risk factors identified at each cut off differed based on a youth's developmental level.

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CHAPTER 4

RESULTS

Hypothesis 1: 1% Absenteeism

Hypothesis 1 utilized CART procedures to identify the most relevant risk factors for problematic school absenteeism defined as equal to or greater than 1% of full school days missed. Youth-related risk factors included age, gender, and ethnicity. Academic-related risk factors included grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), GPA, whether or not a youth was eligible to receive an IEP during the 2015-16 academic year, and whether or not a youth participated in school sports during the 2015-16 academic year. Empirical prior probabilities for problematic school absenteeism were obtained from base rates (i.e., “Yes” = .85, “No” = .15). Probabilities were not adjusted based on custom misclassification costs (i.e., “Yes” = 1.00, “No” = 2.00). Participation in school sports was hypothesized to be most relevant for predicting problematic school absenteeism.

The final tree-model instead identified four relevant risk factors that best differentiated youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from youth with nonproblematic school absenteeism (less than 1% of full school days missed): (1) ethnicity, (2), GPA, (3) grade level, and (4) IEP eligibility (Figure 4). Hypothesis 1 was not supported but the final tree-model did correctly identify 82.7% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism).

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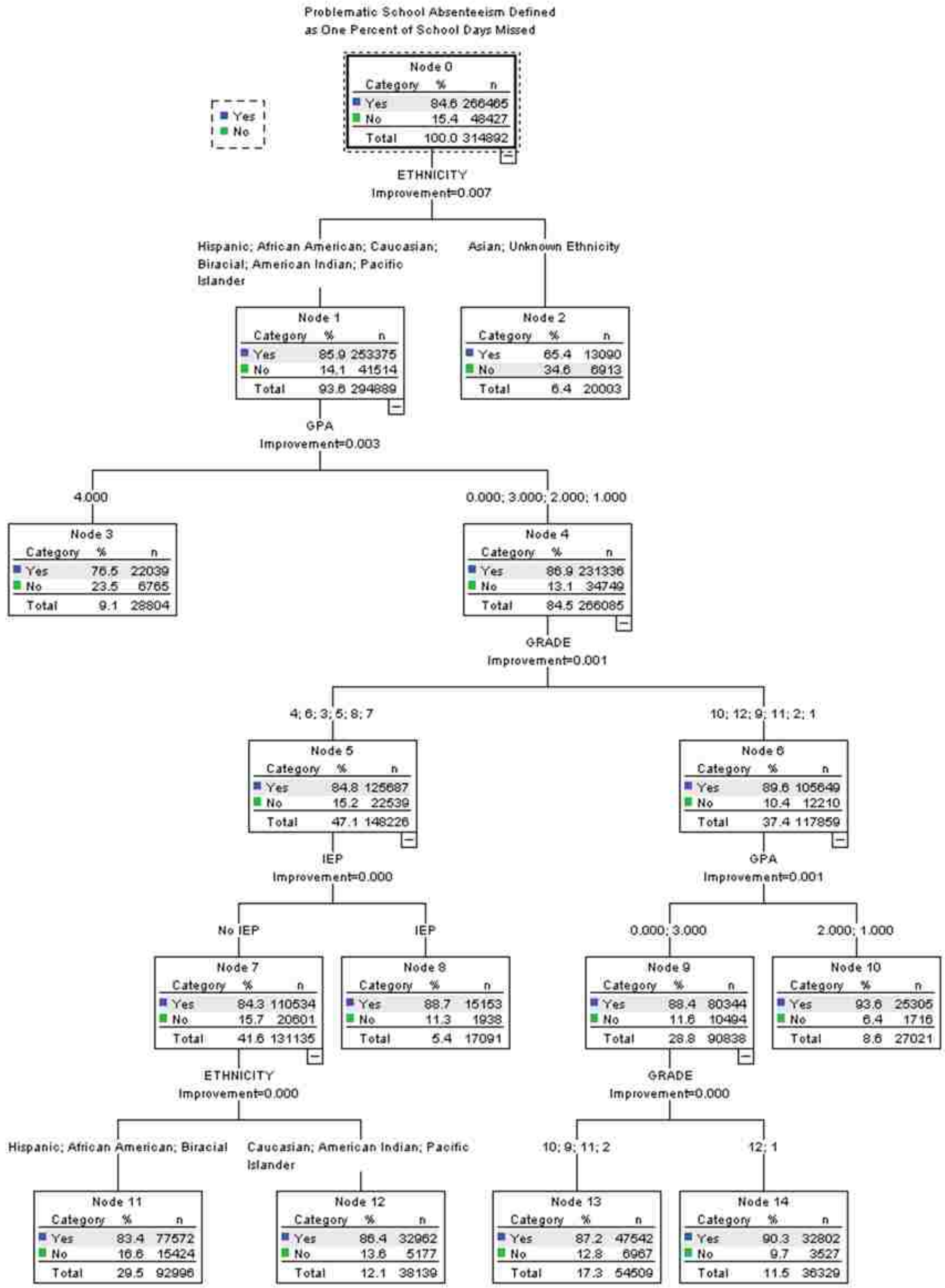

Figure 4. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 1% of full school days missed

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The tree-model classified 95.1% (n = 253,375) of youth with problematic school absenteeism correctly (Table 4). The tree-model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 14.3% (n = 6,913) of youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (r = .305, SE = .001). The tree-model's accuracy in predicting whether a youth outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 69.5%.

Table 4

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	253,375	13,090	95.1%
No	41,514	6,913	14.3%
Overall	93.6%	6.4%	82.7%

Relevant Risk Factors. Eight subgroups associated with varying risk for problematic school absenteeism emerged. Ethnicity was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .007). Ethnicity split such that youth of Asian or unknown ethnicity exhibited a 65.4% (n = 13,090) risk for problematic school absenteeism (Node 2; Terminal). However, youth of Hispanic, African-American, Caucasian, Biracial, American-Indian, or Pacific Islander ethnicity were at a higher risk

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for exhibiting problematic school absenteeism (85.9%; *n* = 253,375; Node 1). GPA was the next most relevant risk factor identified (Gini improvement = .003). For youth in Node 1, GPA split such that earning a GPA between 3.01 and 4.00 was associated with a lower risk for exhibiting problematic school absenteeism (76.5%; *n* = 22,039; Node 3; Terminal). Conversely, earning a GPA between 0.00 and 3.00 or having an unknown/nonexistent GPA placed these youth at an 86.9% (*n* = 231,336) risk for exhibiting problematic school absenteeism (Node 4).

Grade level was the next most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .001). For youth in Node 4, grade level split such that youth in 3^{rd}, 4^{th}, 5^{th}, 6^{th}, 7^{th}, or 8^{th} grade exhibited an 84.8% (*n* = 125,687) risk for problematic school absenteeism (Node 5). However, youth in 1^{st}, 2^{nd}, 9^{th}, 10^{th}, 11^{th}, or 12^{th} grade were at a higher risk for exhibiting problematic school absenteeism (89.6%; *n* = 105,649; Node 6). IEP eligibility was the next most relevant risk factor identified for youth in Node 5 (Gini improvement < .001). Specifically, youth that were not eligible to receive an IEP during the 2015-16 academic year were less likely to exhibit problematic school absenteeism (84.3%; *n* = 110,534; Node 7). However, youth that were eligible to receive an IEP exhibited an 88.7% (*n* = 15,153) risk for problematic school absenteeism (Node 8; Terminal). For youth in Node 7, ethnicity was again identified as a relevant risk factor (Gini improvement < .001). Ethnicity split such that youth of Hispanic, African-American, or Biracial ethnicity exhibited an 83.4% (*n* = 77,572) risk for problematic school absenteeism (Node 11; Terminal). Conversely, youth of Caucasian, American-

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Indian, or Pacific Islander ethnicity were at a higher risk for exhibiting problematic school absenteeism (86.4%; *n* = 32,962; Node 12; Terminal).

For youth in Node 6, GPA was again identified as a relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .001). GPA split such that earning a GPA between 2.01 and 3.00 or having an unknown/nonexistent GPA was associated with a lower risk for exhibiting problematic school absenteeism (88.4%; *n* = 80,344; Node 9). However, earning a GPA between 0.00 and 2.00 placed these youth at a 93.6% (*n* = 25,305) risk for exhibiting problematic school absenteeism (Node 10; Terminal). Grade level was again identified as a relevant risk factor for youth in Node 9 (Gini improvement < .001). Specifically, youth in 2nd, 9th, 10th, or 11th grade were less likely to exhibit problematic school absenteeism (87.2%; *n* = 47,542; Node 13; terminal). Conversely, youth in 1st or 12th grade exhibited a 90.3% (*n* = 32,802) risk for problematic school absenteeism (Node 14; Terminal).

The final tree-model thus identified four relevant risk factors (ethnicity, GPA, grade level, and IEP eligibility) that best differentiated youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from those with nonproblematic school absenteeism (less than 1% of full school days missed). Eight subgroups of youth, each with varying risk for problematic school absenteeism, emerged. Youth of Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander ethnicity with an unknown/nonexistent GPA or GPA between 0.00 and 2.00 in the 1st, 2nd, 9th, 10th, 11th, or 12th grade were identified as the highest risk subgroup for

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problematic school absenteeism. The IF-THEN Rules regarding a youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 5.

Table 5

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed by Risk Probability

	IF	THEN
Node 2	Asian or unknown ethnicity	65.4% probability
Node 3	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND a GPA between 3.01 and 4.00	76.5% probability
Node 11	Hispanic, African American, or Biracial AND an unknown/nonexistent GPA or GPA between 0.00 and 3.00 AND a grade level of 3, 4, 5, 6, 7, or 8 AND no IEP eligibility	83.4% probability
Node 7	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 0.00 and 3.00 AND a grade level of 3, 4, 5, 6, 7, or 8 AND no IEP eligibility	84.3% probability
Node 5	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 0.00 and 3.00 AND a grade level of 3, 4, 5, 6, 7, or 8	84.8% probability
Node 1	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander	85.9% probability
Node 12	Caucasian, American Indian, or Pacific Islander AND an Unknown/ Nonexistent GPA or GPA between 0.00 and 3.00 AND a grade level of 3, 4, 5, 6, 7, or 8 AND no IEP eligibility	86.4% probability
Node 4	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 0.00 and 3.00	86.9% probability
Node 13	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an	87.2% probability

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	unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND a grade level of 2, 9, 10, or 11	
Node 9	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND a grade level of 1, 2, 9, 10, 11, or 12	88.4% probability
Node 8	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 0 and 3.00 AND a grade level of 3, 4, 5, 6, 7, or 8 AND eligible for an IEP	88.7% probability
Node 6	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 0.00 and 3.00 AND a grade level of 1, 2, 9, 10, 11, or 12	89.6% probability
Node 14	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND a grade level of 1 or 12	90.3% probability
Node 10	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 0.00 and 2.00 AND a grade level of 1, 2, 9, 10, 11, or 12	93.6% probability

Hypothesis 2: 10% Absenteeism

Hypothesis 2 utilized CART procedures to identify the most relevant risk factors for problematic school absenteeism defined as equal to or greater than 10% of full school days missed. Youth-related risk factors included age, gender, and ethnicity. Academic-related risk factors included grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), GPA, whether or not a youth was eligible to receive an IEP during the 2015-16 academic year, and whether or not a youth participated

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in school sports during the 2015-16 academic year. Empirical prior probabilities for problematic school absenteeism were obtained from base rates and then adjusted (i.e., "Yes" = .44, "No" = .56). Adjustments were based on custom misclassification costs (i.e., "Yes" = 2.00, "No" = .50). Grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), and GPA were hypothesized to be most relevant for predicting problematic school absenteeism.

The final tree-model instead identified three relevant risk factors that best differentiated youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from youth with nonproblematic school absenteeism (less than 10% of full school days missed): (1) GPA, (2) age, and (3) ethnicity (Figure 5). Hypothesis 2 was partially supported and the final tree-model correctly identified 74.1% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 52.5% (n = 26,963) of youth with problematic school absenteeism correctly (Table 6). The tree-model thus demonstrated lower sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 78.3% (n = 206,458) of youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was adequate (r = .330, SE = .001). The tree-model's accuracy in predicting whether a youth outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 67.0%.

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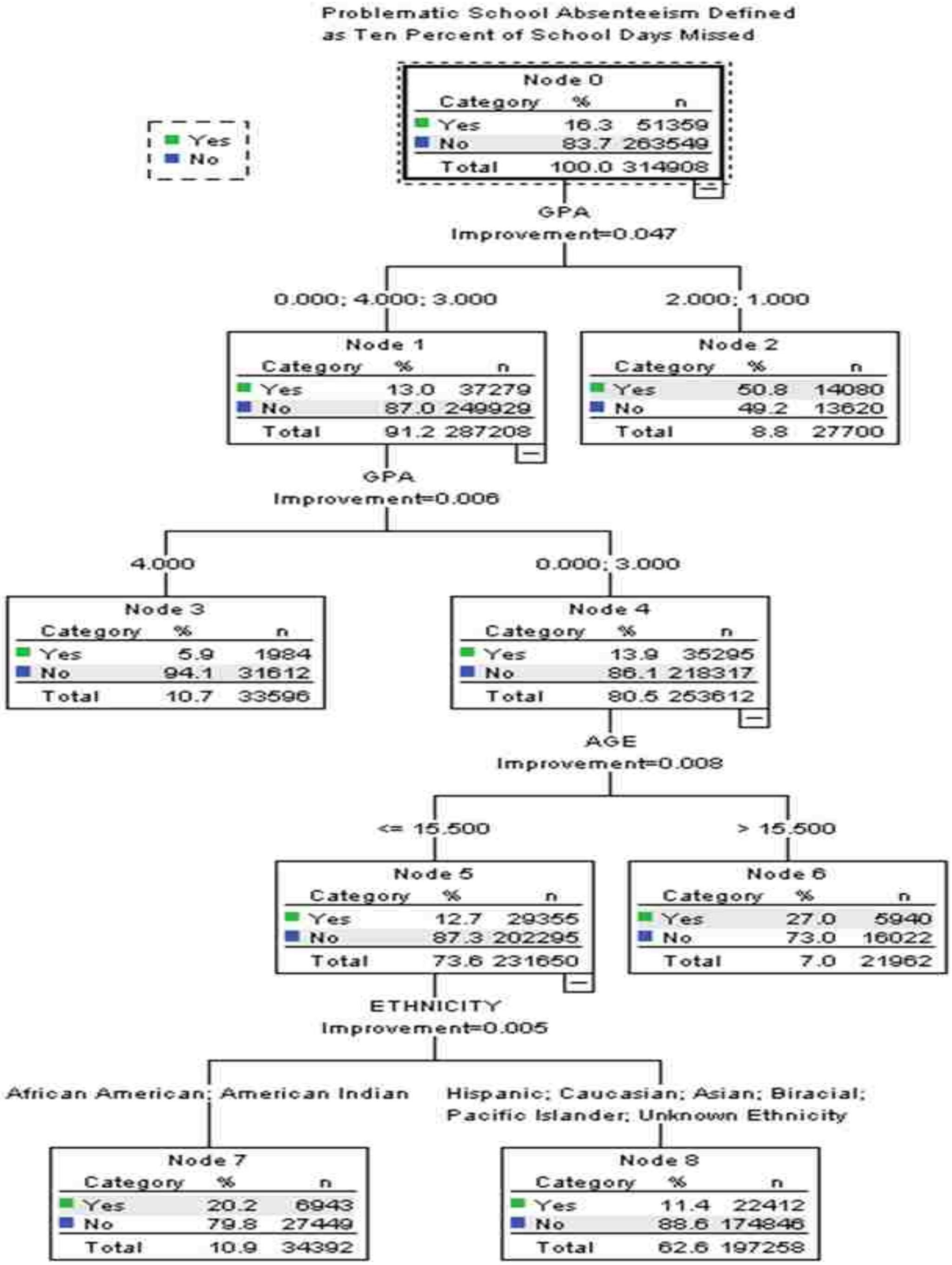

Figure 5. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 10% of full school days missed

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Table 6

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	26,963	24,396	52.5%
No	57,091	206,458	78.3%
Overall	26.7%	73.3%	74.1%

Relevant Risk Factors. Five subgroups associated with varying risk for problematic school absenteeism emerged. GPA was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .047). GPA split such that youth that had earned a GPA between 2.01 and 4.00 or whose GPA was unknown/nonexistent exhibited a 13.0% (n = 37,279) risk for problematic school absenteeism (Node 1). Conversely, youth that had earned a GPA between 0.00 and 2.00 were at a higher risk for exhibiting problematic school absenteeism (50.8%; n = 14,080; Node 2; Terminal). GPA was again identified as a relevant risk factor for youth in Node 1 (Gini improvement = .006). Specifically, earning a GPA between 3.01 and 4.00 was associated with a lower risk for exhibiting problematic school absenteeism (5.9%; n = 1,984; Node 3; Terminal). However, earning a GPA between 2.01 and 3.00 or having an unknown/nonexistent GPA placed these youth at a 13.9% (n = 35,295) risk for problematic school absenteeism (Node 4).

Age was the next most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism

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(Gini improvement = .008). Age split such that youth who were 15.5 years or younger exhibited a 12.7% (n = 29,355) risk for problematic school absenteeism (Node 5). Conversely, youth who were older than 15.5 years of age were at a higher risk for exhibiting problematic school absenteeism (27.0%; n = 5,940; Node 6; Terminal). Ethnicity was the next most relevant risk factor identified (Gini improvement = .005). For youth in Node 5, Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity was associated with a lower risk for exhibiting problematic school absenteeism (11.4%; n = 22,412; Node 8; Terminal). However, being of African American or American Indian ethnicity placed these youth at a 20.2% (n = 6,943) risk for problematic school absenteeism (Node 7; Terminal).

The final tree-model thus identified three relevant risk factors (GPA, age, and ethnicity) that best differentiated youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from those with nonproblematic school absenteeism (less than 10% of full school days missed). Five subgroups of youth, each with varying risk for problematic school absenteeism, emerged. Youth that had earned a GPA between 0.00 and 2.00 were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding a youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 7.

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Table 7

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed by Risk Probability

	IF	THEN
Node 3	A GPA between 3.01 and 4.00	5.9% probability
Node 8	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 15.5 years or younger AND Hispanic, Caucasian, Asian, Pacific Islander, or unknown ethnicity	11.4% probability
Node 5	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 15.5 years or younger	12.7% probability
Node 1	An unknown/nonexistent GPA or GPA between 2.01 and 4.00	13.0% probability
Node 4	An unknown/nonexistent GPA or GPA between 2.01 and 3.00	13.9% probability
Node 7	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 15.5 years or younger AND African American or American Indian	20.2% probability
Node 6	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND older than 15.5 years of age	27.0% probability
Node 2	A GPA between 0.00 and 2.00	50.8% probability

Hypothesis 3: 15% Absenteeism

Hypothesis 3 utilized CART procedures to identify the most relevant risk factors for problematic school absenteeism defined as equal to or greater than 15% of full school days missed. Youth-related risk factors included age, gender, and ethnicity. Academic-related risk factors included grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), GPA, whether or not a youth was eligible to receive an IEP during the 2015-16 academic year, and whether or not a youth participated

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in school sports during the 2015-16 academic year. Empirical prior probabilities for problematic school absenteeism were obtained from base rates and then adjusted (i.e., “Yes” = .49, “No” = .51). Adjustments were based on custom misclassification costs (i.e., “Yes” = 5.00, “No” = .50). Age, gender, and ethnicity were hypothesized to be most relevant for predicting risk of problematic school absenteeism.

The final tree-model instead identified four relevant risk factors that best differentiated youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from youth with nonproblematic school absenteeism (less than 15% of full school days missed): (1) GPA, (2) age, (3) ethnicity, and (4) grade level (Figure 6). Hypothesis 3 was partially supported and the final tree-model correctly identified 75.2% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 61.0% (n = 16,609) of youth with problematic school absenteeism correctly (Table 8). The tree-model thus demonstrated lower sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 76.5% (n = 220,100) of youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (r = .312, SE = .002). The tree-model’s accuracy in predicting whether a youth outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 68.8%.

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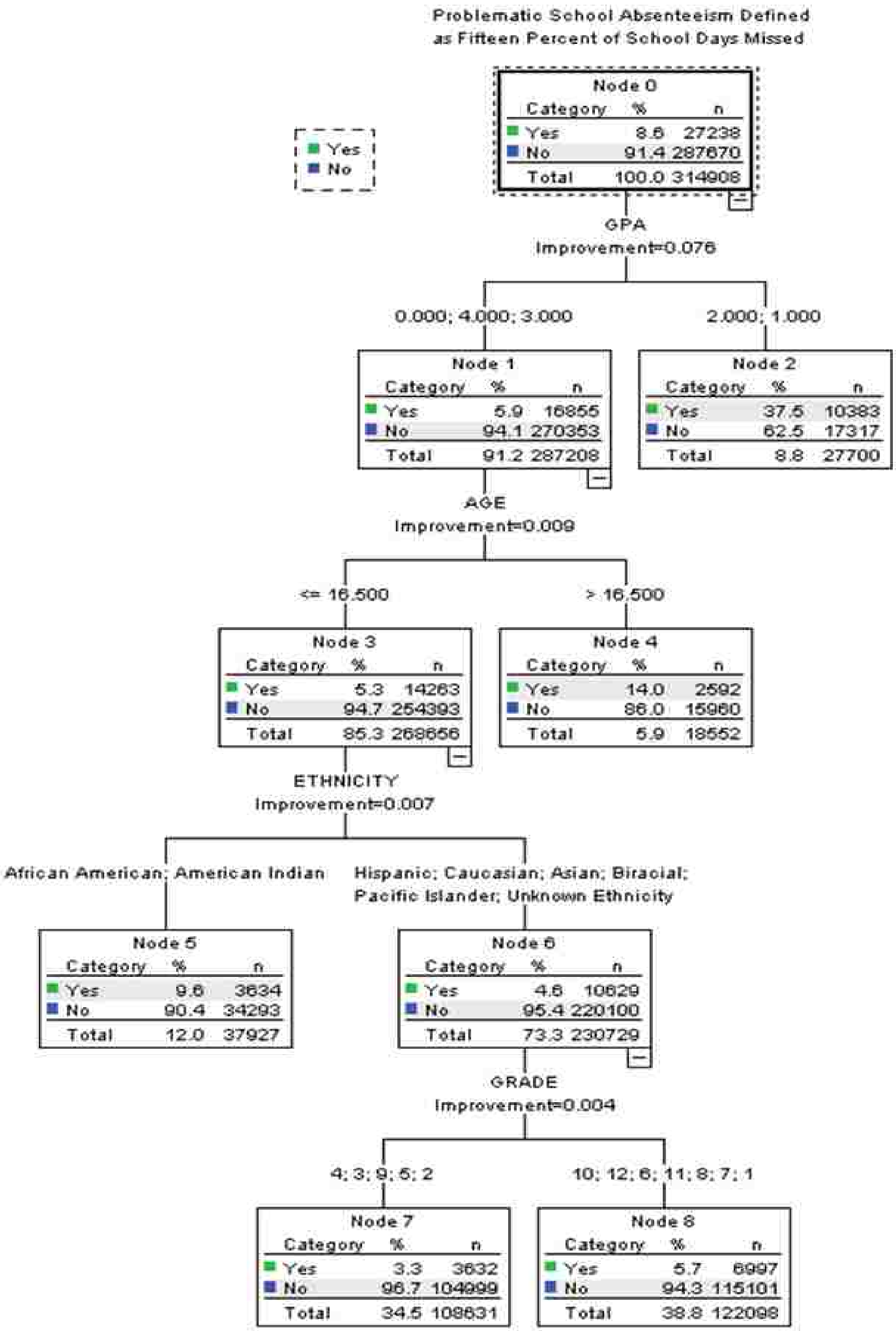

Figure 6. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 15% of full school days missed

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Table 8

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	16,609	10,629	61.0%
No	67,570	220,100	76.5%
Overall	26.7%	73.3%	75.2%

Relevant Risk Factors. Five subgroups associated with varying risk for problematic school absenteeism emerged. GPA was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .076). GPA split such that youth that had earned a GPA between 2.01 and 4.00 or whose GPA was unknown/nonexistent exhibited a 5.9% (n = 16,855) risk for problematic school absenteeism (Node 1). Conversely, youth that had earned a GPA between 0.00 and 2.00 were at a higher risk for exhibiting problematic school absenteeism (37.5%; n = 10,383; Node 2; Terminal). Age was the next most relevant risk factor identified (Gini improvement = .009). Specifically, being age 16.5 years or younger was associated with a lower risk for exhibiting problematic school absenteeism (5.3%; n = 14,263; Node 3). However, being older than 16.5 years of age placed these youth at a 14.0% (n = 2,592) risk for exhibiting problematic school absenteeism (Node 4; Terminal).

Ethnicity was the next most relevant risk factor identified for youth in Node 3. Ethnicity split such that youth of Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity exhibited a 4.6% (n = 10,629) risk for problematic school

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absenteeism (Node 6). Conversely, youth of African American or American Indian ethnicity exhibited a higher risk for problematic school absenteeism (9.6%; *n* = 3,634); Node 5; Terminal). Grade level was the next most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .004). For youth in Node 6, grade level split such that being in 2^{nd}, 3^{rd}, 4^{th}, 5^{th}, or 9^{th} grade was associated with a lower risk for exhibiting problematic school absenteeism (3.3%; *n* = 3,632; Node 7; Terminal). However, being in 1^{st}, 6^{th}, 7^{th}, 8^{th}, 10^{th}, 11^{th}, or 12^{th}, grade placed these youth at a 5.7% (*n* = 6,997) risk for exhibiting problematic school absenteeism (Node 8; Terminal).

The final tree-model thus identified four relevant risk factors (GPA, age, ethnicity, and grade level) that best differentiated youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from those with nonproblematic school absenteeism (less than 15% of full school days missed). Five subgroups of youth, each with varying risk for problematic school absenteeism, emerged. Youth that had earned a GPA between 0.00 and 2.00 were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding a youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 9.

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Table 9

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed by Risk Probability

	IF	THEN
Node 7	Unknown/nonexistent GPA or a GPA between 2.01 and 4.00 AND age 16.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity AND a grade level of 2, 3, 4, 5, or 9	3.3% probability
Node 6	Unknown/nonexistent GPA or a GPA between 2.01 and 4.00 AND age 16.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity	4.6% probability
Node 3	Unknown/nonexistent GPA or a GPA between 2.01 and 4.00 AND age 16.5 years or younger	5.3% probability
Node 8	Unknown/nonexistent GPA or a GPA between 2.01 and 4.00 AND age 16.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity AND a grade level of 1, 6, 7, 8, 10, 11, or 12	5.7% probability
Node 1	Unknown/nonexistent GPA or a GPA between 2.01 and 4.00	5.9% probability
Node 5	Unknown/nonexistent GPA or a GPA between 2.01 and 4.00 AND age 16.5 years or younger AND African American or American Indian	9.6% probability
Node 4	Unknown/nonexistent GPA or a GPA between 2.01 and 4.00 AND older than 16.5 years of age	14.0% probability
Node 2	GPA between 0.00 and 2.00	37.5% probability

Post Hoc Analyses

Several post hoc analyses were conducted given the exploratory nature of recursive partitioning techniques. CART was employed at different developmental levels (i.e., elementary vs. middle vs. high school). Specifically, three classification tree-models

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were constructed for each developmental level, one to represent each of the distinct cutoffs for problematic school absenteeism (1%, 10%, and 15% of full school days missed). The present study examined whether the most relevant risk factors identified at each cut off differed based on a youth's developmental level.

Elementary Youth. CART procedures were employed to identify the most relevant risk factors for problematic school absenteeism defined at three distinct cutoffs in elementary school youth based on certain (1) youth- (age, gender, and ethnicity) and (2) academic-related (grade level and whether or not a youth was eligible to receive an IEP during the 2015-16 academic year) variables. Unequal distribution of group membership was observed at each of the three distinct cutoffs for problematic school absenteeism. For example, the base rate of problematic school absenteeism defined as 1% of full school days missed in elementary school youth was 86.2% (n = 116,056). The base rate of problematic school absenteeism defined as 10% of full school days missed in elementary school youth was 11.8% (n = 15,892). The base rate of problematic school absenteeism defined as 15% of full school days missed in elementary school youth was 4.5% (n = 6,125). These sample distributions of problematic school absenteeism are expected to be representative of the population distribution. Empirical prior probabilities were thus obtained. Probabilities were adjusted based on misclassification costs in some tree-models to enhance predictive validity.

One Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 1% of full school days missed were obtained from base rates (i.e., "Yes" = .86, "No" = .14). Probabilities were not adjusted based on custom misclassification costs (i.e., "Yes" = .50, "No" = 2.00). The final tree-model identified

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two relevant risk factors that best differentiated elementary school youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from elementary school youth with nonproblematic school absenteeism (less than 1% of full school days missed): (1) ethnicity and (2) grade level (Figure 7). The final tree-model correctly identified 83.8% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 95.5% (*n* = 110,831) of elementary school youth with problematic school absenteeism correctly (Table 10). The tree-model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 10.6% (*n* = 1,977) of elementary school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (r = .277, SE = .002). The tree-model's accuracy in predicting whether a youth in elementary school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 72.3%.

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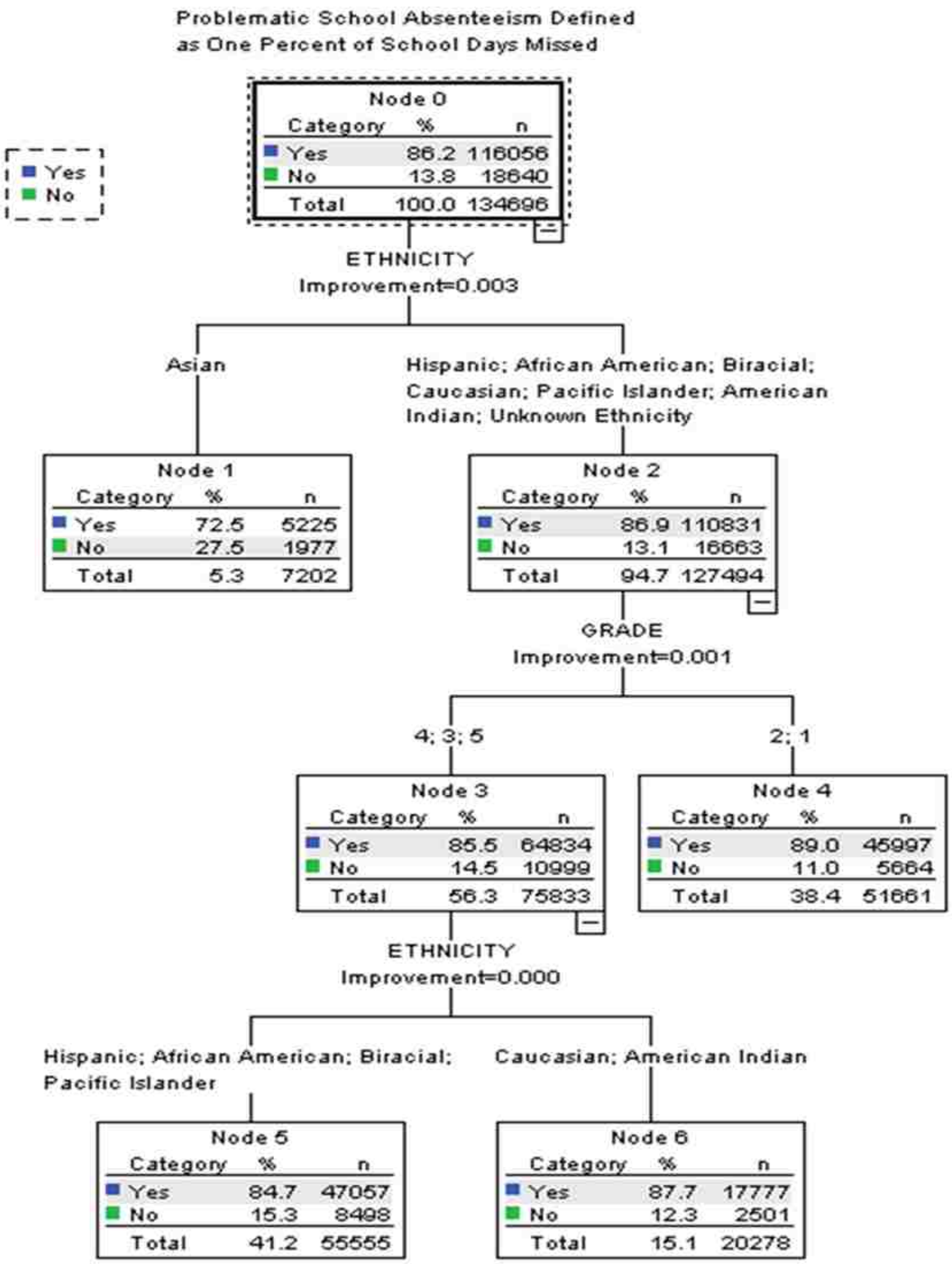

Figure 7. Elementary school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 1% of full school days missed

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Table 10

Elementary School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	110,831	5,225	95.5%
No	16,663	1,977	10.6%
Overall	94.7%	5.3%	83.8%

Four subgroups associated with varying risk for problematic school absenteeism emerged. Ethnicity was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .003). Ethnicity split such that Asian youth exhibited a 72.5% (*n* = 5,225) risk for problematic school absenteeism (Node 1; Terminal). Conversely, youth of Hispanic, African American, Biracial, Caucasian, Pacific Islander, American Indian, or unknown ethnicity were at a higher risk for exhibiting problematic school absenteeism (86.9%; *n* = 110,831; Node 2). Grade level was the next most relevant risk factor identified (Gini improvement = .001). For youth in Node 2, being in 3rd, 4th, or 5th grade was associated with a lower risk for exhibiting problematic school absenteeism (85.5%; *n* = 64,834; Node 3). However, being in 1st or 2nd grade placed these youth at an 89.0% (*n* = 45,997) risk for exhibiting problematic school absenteeism (Node 4; Terminal). Ethnicity was again identified as a relevant risk factor for youth in Node 3 (Gini improvement < .001). Specifically, youth of Hispanic, African American, Biracial, or Pacific Islander ethnicity exhibited an 84.7% (*n* = 47,057) risk for problematic school absenteeism (Node 5; Terminal). Conversely, youth of Caucasian or American Indian

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ethnicity were more likely to exhibit problematic school absenteeism (87.7%; *n* = 17,777; Node 6; Terminal).

The final tree-model thus identified two relevant risk factors (ethnicity and grade level) that best differentiated elementary school youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from those with nonproblematic school absenteeism (less than 1% of full school days missed). Four subgroups of elementary school youth, each with varying risk for problematic school absenteeism, emerged. Youth of Hispanic, African American, Biracial, Caucasian, Pacific Islander, American Indian, or unknown ethnicity in the 1st or 2nd grade were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding an elementary school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 11.

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Table 11

Elementary School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed by Risk Probability

	IF	THEN
Node 1	Asian	72.5% probability
Node 5	Hispanic, African American, Biracial, or Pacific Islander AND a grade level of 3, 4, or 5	84.7% probability
Node 3	Hispanic, African American, Biracial, Caucasian, Pacific Islander, American Indian, or unknown ethnicity AND a grade level of 3, 4, or 5	85.5% probability
Node 2	Hispanic, African American, Biracial, Caucasian, Pacific Islander, American Indian, or unknown ethnicity	86.9% probability
Node 6	Caucasian or American Indian AND a grade level of 3, 4, or 5	87.7% probability
Node 4	Hispanic, African American, Biracial, Caucasian, Pacific Islander, American Indian, or unknown ethnicity AND a grade level of 1 or 2	89.0% probability

Ten Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 10% of full school days missed were obtained from base rates (i.e., “Yes” = .12, “No” = .88). Probabilities were not adjusted based on custom misclassification costs (i.e., “Yes” = .30, “No” = 2.50). The final tree-model identified three relevant risk factors that best differentiated elementary school youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from elementary school youth with nonproblematic school absenteeism (less than 10% of full school days missed): (1) ethnicity, (2) grade level, and (3) IEP eligibility (Figure 8).

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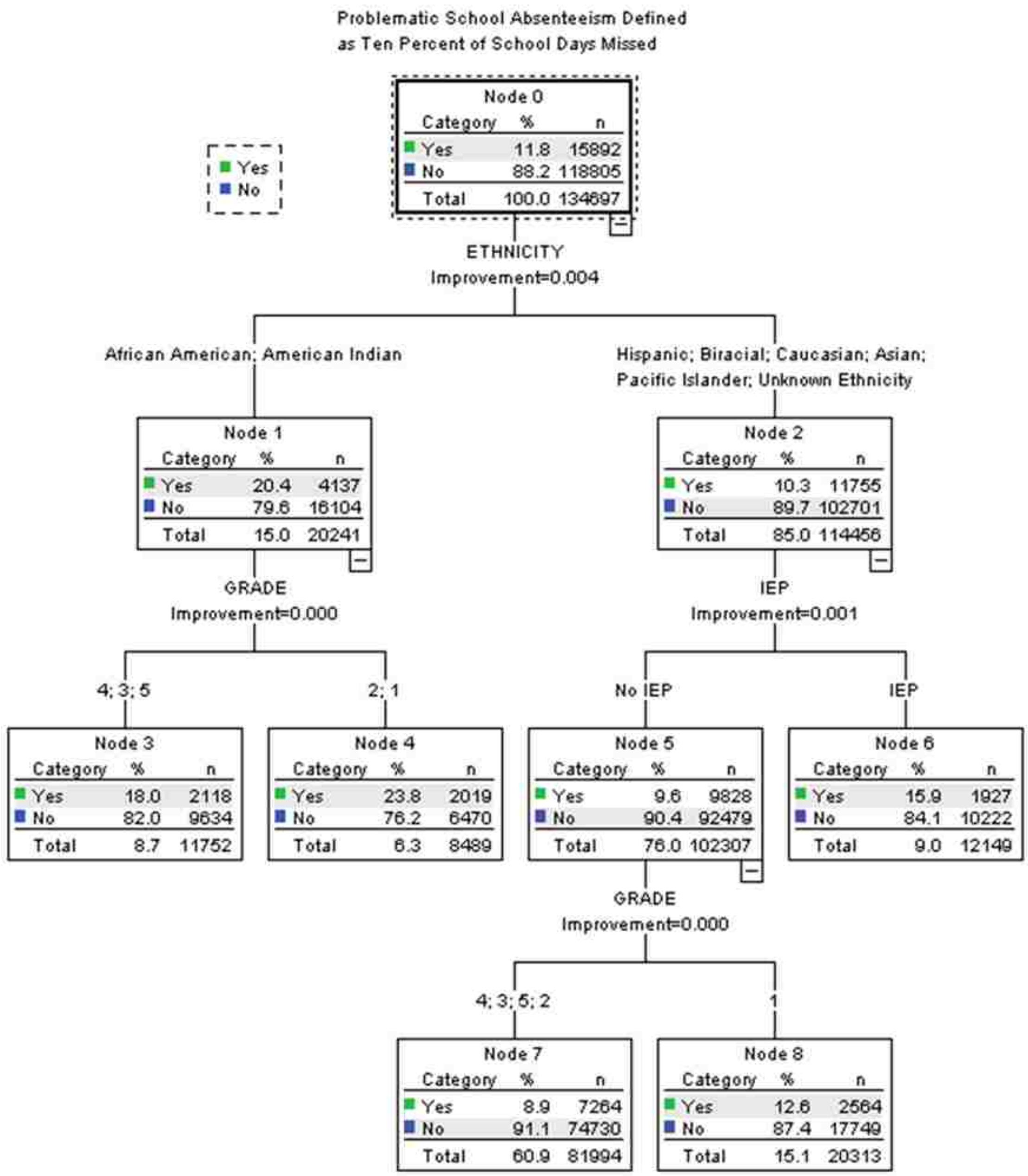

Figure 8. Elementary school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 10% of full school days missed

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The final tree-model correctly identified 61.9% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 54.3% (*n* = 8,628) of elementary school youth with problematic school absenteeism correctly (Table 12). The tree-model thus demonstrated lower sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 62.9% (*n* = 74,730) of elementary school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (*r* = .233, *SE* = .002). The tree-model's accuracy in predicting whether a youth in elementary school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 76.7%.

Table 12

Elementary School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed

Problematic School	Predicted		Percent Correct
Absenteeism	*Yes*	*No*	
Yes	8,628	7,264	54.3%
No	44,0075	74,730	62.9%
Overall	39.1%	60.9%	61.9%

Five subgroups associated with varying risk for problematic school absenteeism emerged. Ethnicity was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .004). Ethnicity split such that youth of Hispanic, Biracial, Caucasian, Asian, Pacific Islander, or unknown ethnicity exhibited a 10.3% (*n* = 11,755)

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risk for problematic school absenteeism (Node 2). However, youth of African American or American Indian ethnicity were at a higher risk for exhibiting problematic school absenteeism (20.4%; n = 4,137; Node 1). Grade level was the next most relevant risk factor for youth in Node 1 (Gini improvement < .001). Specifically, youth in 3rd, 4th, or 5th grade were less likely to exhibit problematic school absenteeism (18.0%; n = 2,118; Node 3; Terminal). Conversely, youth in 1st or 2nd grade exhibited a 23.8% (n = 2,019) risk for problematic school absenteeism (Node 4; Terminal).

For youth in Node 2, IEP eligibility was the next most relevant risk factor identified (Gini improvement = .001). Specifically, youth that were not eligible to receive an IEP during the 2015-16 academic year exhibited a 9.6% (n = 9,828) risk for problematic school absenteeism (Node 5). However, youth that were eligible to receive an IEP were at a higher risk for exhibiting problematic school absenteeism (15.9%; n = 1,927; Node 6; Terminal). Grade level was the next most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement < .001). For youth in Node 5, grade level split such that being in 2nd, 3rd, 4th, or 5th grade was associated with a lower risk for exhibiting problematic school absenteeism (8.9%; n = 7,264; Node 7; Terminal). Conversely, being in 1st grade placed these youth at a 12.6% (n = 2,564) risk for exhibiting problematic school absenteeism (Node 8; Terminal).

The final tree-model thus identified three relevant risk factors (ethnicity, grade level, and IEP eligibility) that best differentiated elementary school youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from those with nonproblematic school absenteeism (less than 10% of full school days

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missed). Five subgroups of elementary school youth, each with varying risk for problematic school absenteeism, emerged. Youth of African American or American Indian ethnicity in the 1st or 2nd grade were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding an elementary school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 13.

Table 13

Elementary School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed by Risk Probability

	IF	THEN
Node 7	Hispanic, Biracial, Caucasian, Pacific Islander, or unknown ethnicity AND no IEP eligibility AND a grade level of 2, 3, 4, or 5	8.9% probability
Node 5	Hispanic, Biracial, Caucasian, Pacific Islander, or unknown ethnicity AND no IEP eligibility	9.6% probability
Node 2	Hispanic, Biracial, Caucasian, Pacific Islander, or unknown ethnicity	10.3% probability
Node 8	Hispanic, Biracial, Caucasian, Pacific Islander, or unknown ethnicity AND no IEP eligibility AND a grade level of 1	12.6% probability
Node 6	Hispanic, Biracial, Caucasian, Pacific Islander, or unknown ethnicity AND eligible for IEP	15.9% probability
Node 3	African American or American Indian AND a grade level of 3, 4, or 5	18.0% probability
Node 1	African American or American Indian	20.4% probability
Node 4	African American or American Indian AND a grade level of 1 or 2	23.8% probability

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Fifteen Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 15% of full school days missed were obtained from base rates and then adjusted (i.e., “Yes” = .50, “No” = .50). Adjustments were based on custom misclassification costs (i.e., “Yes” = 2.10, “No” = .10). The final tree-model identified three relevant risk factors that best differentiated elementary school youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from elementary school youth with nonproblematic school absenteeism (less than 15% of full school days missed): (1) ethnicity, (2) grade level, and (3) IEP eligibility (Figure 9). The final tree-model correctly identified 62.5% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 58.2% (n = 3,564) of elementary school youth with problematic school absenteeism correctly (Table 14). The tree-model thus demonstrated lower sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 62.7% (n = 80,640) of elementary school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was adequate (r = .396, SE = .003). The tree-model’s accuracy in predicting whether a youth in elementary school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 60.4%.

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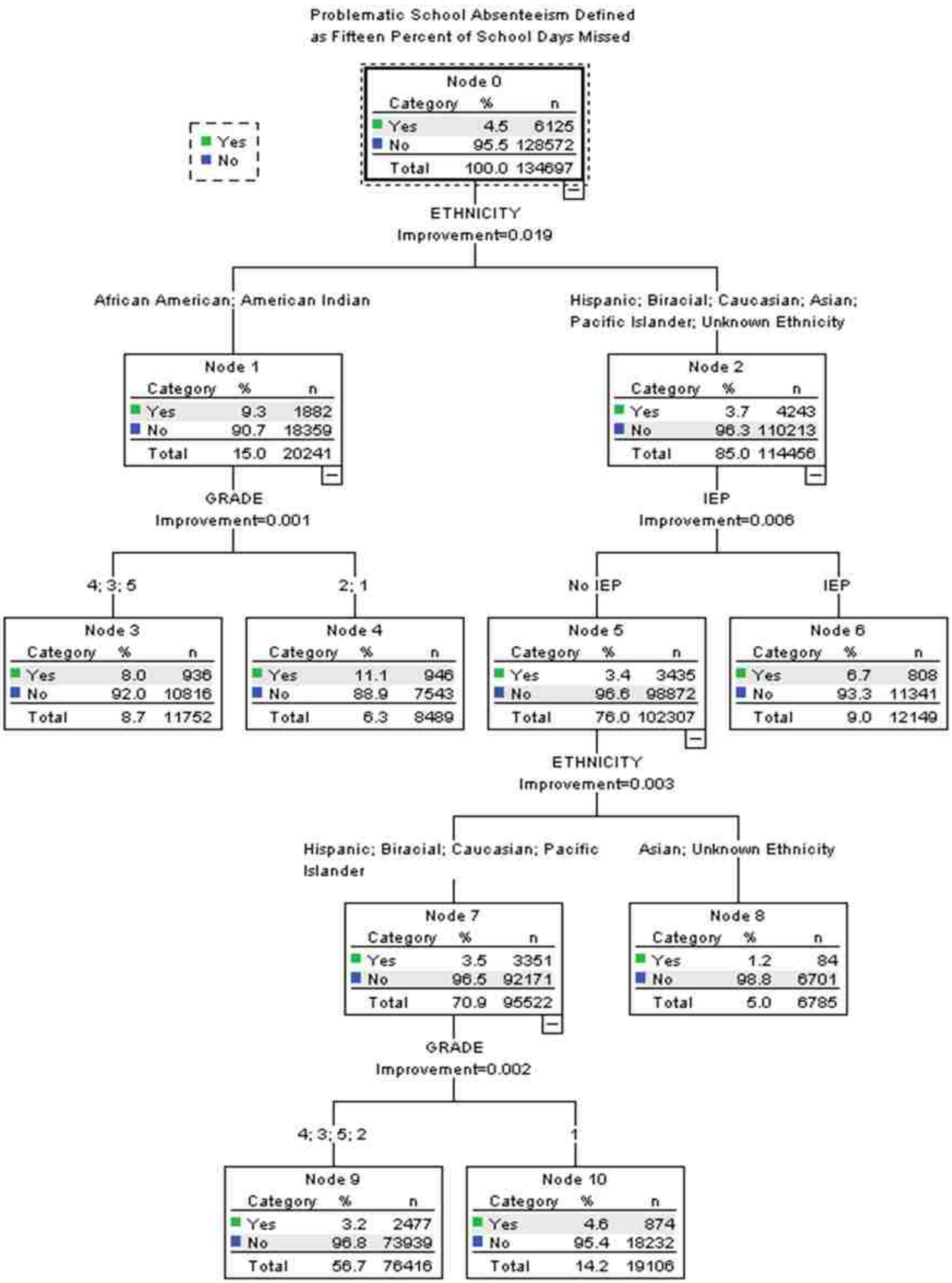

Figure 9. Elementary school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 15% of full school days missed

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Table 14

Elementary School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	*No*	Percent Correct
Yes	3,564	2,561	58.2%
No	47,932	80,640	62.7%
Overall	38.2%	61.8%	62.5%

Six subgroups associated with varying risk for problematic school absenteeism emerged. Ethnicity was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .019). Ethnicity split such that youth of Hispanic, Biracial, Caucasian, Asian, Pacific Islander, or unknown ethnicity exhibited a 3.7% (n = 4,243) risk for problematic school absenteeism (Node 2). Conversely, youth of African American or American Indian ethnicity were at a higher risk for exhibiting problematic school absenteeism (9.3%; n = 1,882; Node 1). Grade level was the next most relevant risk factor identified for youth in Node 1 (Gini improvement = .001). Specifically, being in 3rd, 4th, or 5th grade was associated with a lower risk for exhibiting problematic school absenteeism (8.0%; n = 936; Node 3; Terminal). However, being in 1st or 2nd grade placed these youth at an 11.1% (n = 946) risk for exhibiting problematic school absenteeism (Node 4; Terminal).

For youth in Node 2, IEP eligibility was the next most relevant risk factor identified (Gini improvement = .006). Youth that were not eligible to receive an IEP during the 2015-16 academic year exhibited a 3.4% (n = 3,435) risk for problematic

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school absenteeism (Node 5). Conversely, youth that were eligible to receive an IEP were at a higher risk for exhibiting problematic school absenteeism (6.7%; *n* = 808; Node 6; Terminal). Ethnicity was again identified as a relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .003). For youth in Node 5, being of Asian or unknown ethnicity was associated with a lower risk for exhibiting problematic school absenteeism (1.2%; *n* = 84; Node 8; Terminal). However, being of Hispanic, Biracial, Caucasian, or Pacific Islander ethnicity placed these youth at a 3.5% (*n* = 3,351) risk for exhibiting problematic school absenteeism (Node 7). Grade level was the next most relevant risk factor identified for youth in Node 7 (Gini improvement = .002). Specifically, youth in 2nd, 3rd, 4th, or 5th grade exhibited a 3.2% (*n* = 2,477) risk for problematic school absenteeism (Node 9; Terminal). Conversely, youth in 1st grade were at a higher risk for exhibiting problematic school absenteeism (4.6%; *n* = 874; Node 10; Terminal).

The final tree-model thus identified three relevant risk factors (ethnicity, grade level, and IEP eligibility) that best differentiated elementary school youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from those with nonproblematic school absenteeism (less than 15% of full school days missed. Six subgroups of elementary school youth, each with varying risk for problematic school absenteeism, emerged. Youth of African American or American Indian ethnicity in the 1st or 2nd grade were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding an elementary school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 15.

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Table 15

Elementary School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed by Risk Probability

	IF	THEN
Node 8	Asian or unknown ethnicity AND no IEP eligibility	1.2% probability
Node 9	Hispanic, Biracial, Caucasian, Asian, Pacific Islander or unknown ethnicity AND no IEP eligibility AND a grade level of 2, 3, 4, or 5	3.2% probability
Node 5	Hispanic, Biracial, Caucasian, or Pacific Islander AND no IEP eligibility	3.4% probability
Node 7	Hispanic, Biracial, Caucasian, Asian, Pacific Islander or unknown ethnicity AND no IEP eligibility	3.5% probability
Node 2	Hispanic, Biracial, Caucasian, Asian, Pacific Islander or unknown ethnicity	3.7% probability
Node 10	Hispanic, Biracial, Caucasian, Asian, Pacific Islander or unknown ethnicity AND no IEP eligibility AND a grade level of 1	4.6% probability
Node 6	Hispanic, Biracial, Caucasian, Asian, Pacific Islander or unknown ethnicity AND eligible for an IEP	6.7% probability
Node 3	African American or American Indian AND a grade level of 3, 4, or 5	8.0% probability
Node 1	African American or American Indian	9.3% probability
Node 4	African American or American Indian AND a grade level of 1 or 2	11.1% probability

Middle School Youth. CART procedures were employed to identify the most relevant risk factors for problematic school absenteeism defined at three distinct cutoffs in middle school youth based on certain (1) youth- (age, gender, and ethnicity) and (2) academic-related (grade level, whether or not a youth was eligible to receive an IEP during the 2015-16 academic year, and whether or not a youth participated in school

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sports during the 2015-16 academic year) variables. Unequal distribution of group membership was observed at each of the three distinct cutoffs for problematic school absenteeism. For example, the base rate of problematic school absenteeism defined as 1% of full school days missed in middle school youth was 82.3% (n = 63,772). The base rate of problematic school absenteeism defined as 10% of full school days missed in middle school youth was 13.9% (n = 10,799). The base rate of problematic school absenteeism defined as 15% of full school days missed in middle school youth was 7.0% (n = 5,408). These sample distributions of problematic school absenteeism are expected to be representative of the population distribution. Empirical prior probabilities were thus obtained. Probabilities were adjusted based on misclassification costs in some tree-models to enhance predictive validity.

One Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 1% of full school days missed were obtained from base rates (i.e., "Yes" = .82, "No" = .18). Probabilities were not adjusted based on custom misclassification costs (i.e., "Yes" = .50, "No" = 1.5). The final tree-model identified two relevant risk factors that best differentiated middle school youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from middle school youth with nonproblematic school absenteeism (less than 1% of full school days missed): (1) ethnicity and (2) IEP eligibility (Figure 10). The final tree-model correctly identified 81.3% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 95.4% (n = 60,853) of middle school youth with problematic school absenteeism correctly (Table 16). The tree-model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e.,

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true negative rate; 15.7% (n = 2,152) of middle school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (r = .242, SE = .002). The tree-model's accuracy in predicting whether a youth in middle school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 75.8%.

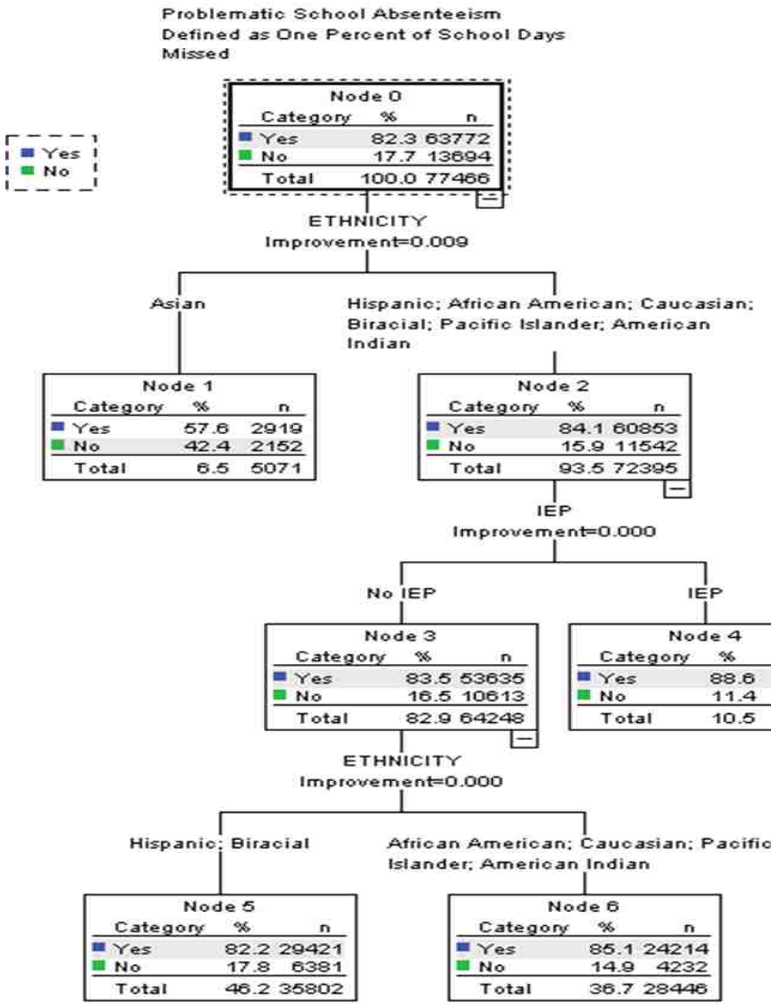

Figure 10. Middle school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 1% of full school days missed

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Table 16

Middle School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	60,853	2,919	95.4%
No	11,542	2,152	15.7%
Overall	93.5%	6.5%	81.3%

Four subgroups associated with varying risk for problematic school absenteeism emerged. Ethnicity was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .009). Ethnicity split such that Asian youth exhibited a 57.6% (*n* = 2,919) risk for problematic school absenteeism (Node 1; Terminal). Conversely, youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity were at a higher risk for exhibiting problematic school absenteeism (84.1%; *n* = 60,853; Node 2). IEP eligibility was the next most relevant risk factor identified (Gini improvement < .001). Specifically, youth that were not eligible to receive an IEP during the 2015-16 academic year were less likely to exhibit problematic school absenteeism (83.5%; *n* = 7,218; Node 3). However, youth that were eligible to receive an IEP exhibited an 88.6% (*n* = 53,635) risk for problematic school absenteeism (Node 4; Terminal). Ethnicity was again identified as a relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement < .001). For youth in Node 3, ethnicity split such that Hispanic or Biracial youth exhibited an 82.2% (*n* = 29,421) risk for problematic school

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absenteeism (Node 5; Terminal). Conversely, youth of African American, Caucasian, Pacific Islander, or American Indian ethnicity were at a higher risk for exhibiting problematic school absenteeism (85.1%; n = 24,214; Node 6; Terminal).

The final tree-model thus identified two relevant risk factors (ethnicity and IEP eligibility) that best differentiated middle school youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from those with nonproblematic school absenteeism (less than 1% of full school days missed). Four subgroups of middle school youth, each with varying risk for problematic school absenteeism, emerged. Youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity that were eligible for an IEP during the 2015-16 academic year were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding a middle school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 17.

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Table 17

Middle School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed by Risk Probability

	IF	THEN
Node 1	Asian ethnicity	57.6% probability
Node 5	Hispanic or Biracial ethnicity	82.2% probability
Node 3	Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity AND no IEP eligibility	83.5% probability
Node 2	Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity	84.1% probability
Node 6	African American, Caucasian, Pacific Islander, or American Indian ethnicity	85.1% probability
Node 4	Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity AND eligible for an IEP	88.6% probability

Ten Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 10% of full school days missed were obtained from base rates and then adjusted (i.e., “Yes” = .76, “No” = .24). Adjustments were based on custom misclassification costs (i.e., “Yes” = 4.00, “No” = .20). The final tree-model identified one relevant risk factor that best differentiated middle school youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from middle school youth with nonproblematic school absenteeism (less than 10% of full school days missed): (1) ethnicity (Figure 11). The final tree-model correctly identified 20.0% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 98.4% (n = 10,626) of middle school youth with problematic school absenteeism correctly (Table 18). The tree-model thus demonstrated

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higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 7.3% (n = 4,898) of middle school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (r = .231, SE = .001). The tree-model's accuracy in predicting whether a youth in middle school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 76.9%.

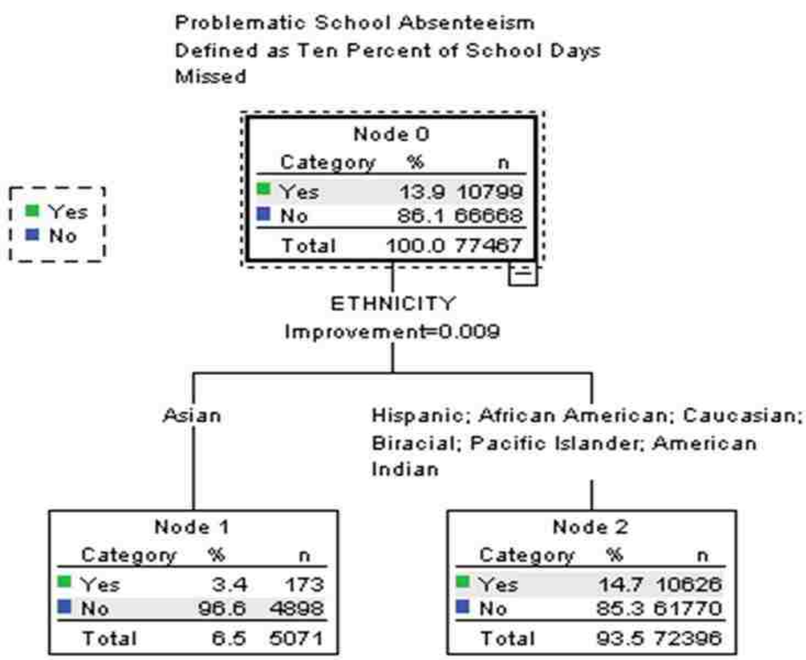

Figure 11. Middle school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 10% of full school days missed

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Table 18

Middle School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	*No*	Percent Correct
Yes	10,626	173	98.4%
No	61,770	4,898	7.3%
Overall	93.5%	6.5%	20.0%

Two subgroups associated with varying risk for problematic school absenteeism emerged. Ethnicity was the only relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .007). Ethnicity split such that Asian youth exhibited a 3.4% (n = 173) risk for problematic school absenteeism (Node 1; Terminal). Conversely, youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity were at a higher risk for exhibiting problematic school absenteeism (14.7%; n = 10,626; Node 2; Terminal).

The final tree-model thus identified one relevant risk factor (ethnicity) that best differentiated middle school youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from those with nonproblematic school absenteeism (less than 10% of full school days missed. Two subgroups of middle school youth, each with varying risk for problematic school absenteeism, emerged. Youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity were identified as the highest risk subgroup for problematic school absenteeism.

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The IF-THEN Rules regarding a middle school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 19.

Table 19

Middle School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed by Risk Probability

	IF	THEN
Node 1	Asian ethnicity	3.4% probability
Node 2	Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity	14.7% probability

Fifteen Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 15% of full school days missed were obtained from base rates and then adjusted (i.e., "Yes" = .77, "No" = .23). Adjustments were based on custom misclassification costs (i.e., "Yes" = 4.50, "No" = .10). The final tree-model identified one relevant risk factor that best differentiated middle school youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from middle school youth with nonproblematic school absenteeism (less than 15% of full school days missed): (1) ethnicity (Figure 12).

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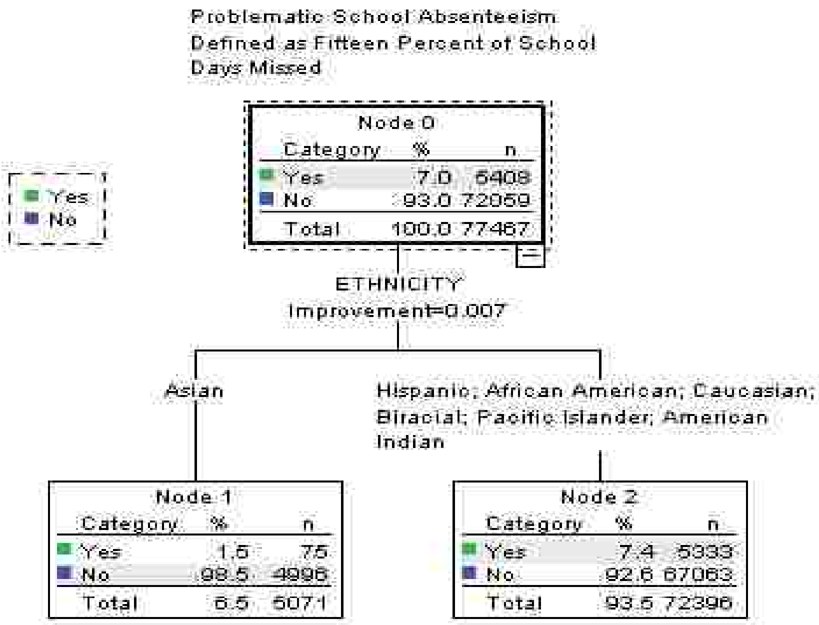

Figure 12. Middle school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 15% of full school days missed

The final tree-model correctly identified 13.3% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 98.6% (*n* = 5,333) of middle school youth with problematic school absenteeism correctly (Table 20). The tree-model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 6.9% (*n* = 4,996) of middle school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (*r* = .223, *SE* = .001). The tree-model's accuracy in predicting whether a youth in middle school outside this sample will exhibit

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problematic school absenteeism (i.e., after misclassification costs) is approximately 77.7%.

Table 20

Middle School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	*No*	Percent Correct
Yes	5,333	75	98.6%
No	67,063	4,996	6.9%
Overall	93.5%	6.5%	13.3%

Two subgroups associated with varying risk for problematic school absenteeism emerged. Ethnicity was the only relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .007). Ethnicity split such that Asian youth exhibited a 1.5% (n = 75) risk for problematic school absenteeism (Node 1; Terminal). Conversely, youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity were at a higher risk for exhibiting problematic school absenteeism (7.4%; n = 5,333; Node 2; Terminal).

The final tree-model thus identified one relevant risk factor (ethnicity) that best differentiated middle school youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from those with nonproblematic school absenteeism (less than 15% of full school days missed). Two subgroups of middle school

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youth, each with varying risk for problematic school absenteeism, emerged. Youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding a middle school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 21.

Table 21

Middle School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed by Risk Probability

	IF	THEN
Node 1	Asian ethnicity	1.5% probability
Node 2	Hispanic, African American, Caucasian, Biracial, Pacific Islander, or American Indian ethnicity	7.4% probability

High School Youth. CART procedures were employed to identify the most relevant risk factors for problematic school absenteeism defined at three distinct cutoffs in high school youth based on certain (1) youth- (age, gender, and ethnicity) and (2) academic-related (grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), GPA, whether or not a youth was eligible to receive an IEP during the 2015-16 academic year, and whether or not a youth participated in school sports during the 2015-16 academic year) variables. Unequal distribution of group membership was observed at each of the three distinct cutoffs for problematic school

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absenteeism. For example, the base rate of problematic school absenteeism defined as 1% of full school days missed in high school youth was 84.3%% (*n* = 86,637). The base rate of problematic school absenteeism defined as 10% of full school days missed in high school youth was 24.0% (*n* = 24,668). The base rate of problematic school absenteeism defined as 15% of full school days missed in high school youth was 15.3% (*n* = 15,705). These sample distributions of problematic school absenteeism are expected to be representative of the population distribution. Empirical prior probabilities were thus obtained. Probabilities were adjusted based on misclassification costs in some tree-models to enhance the predictive validity.

One Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 1% of full school days missed were obtained from base rates (i.e., "Yes" = .84, "No" = .16). Probabilities were not adjusted based on custom misclassification costs (i.e., "Yes" = .50, "No" = 2.00). The final tree-model identified two relevant risk factors that best differentiated high school youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from high school youth with problematic school absenteeism (less than 1% of full school days missed): (1) GPA and (2) gender (Figure 13).

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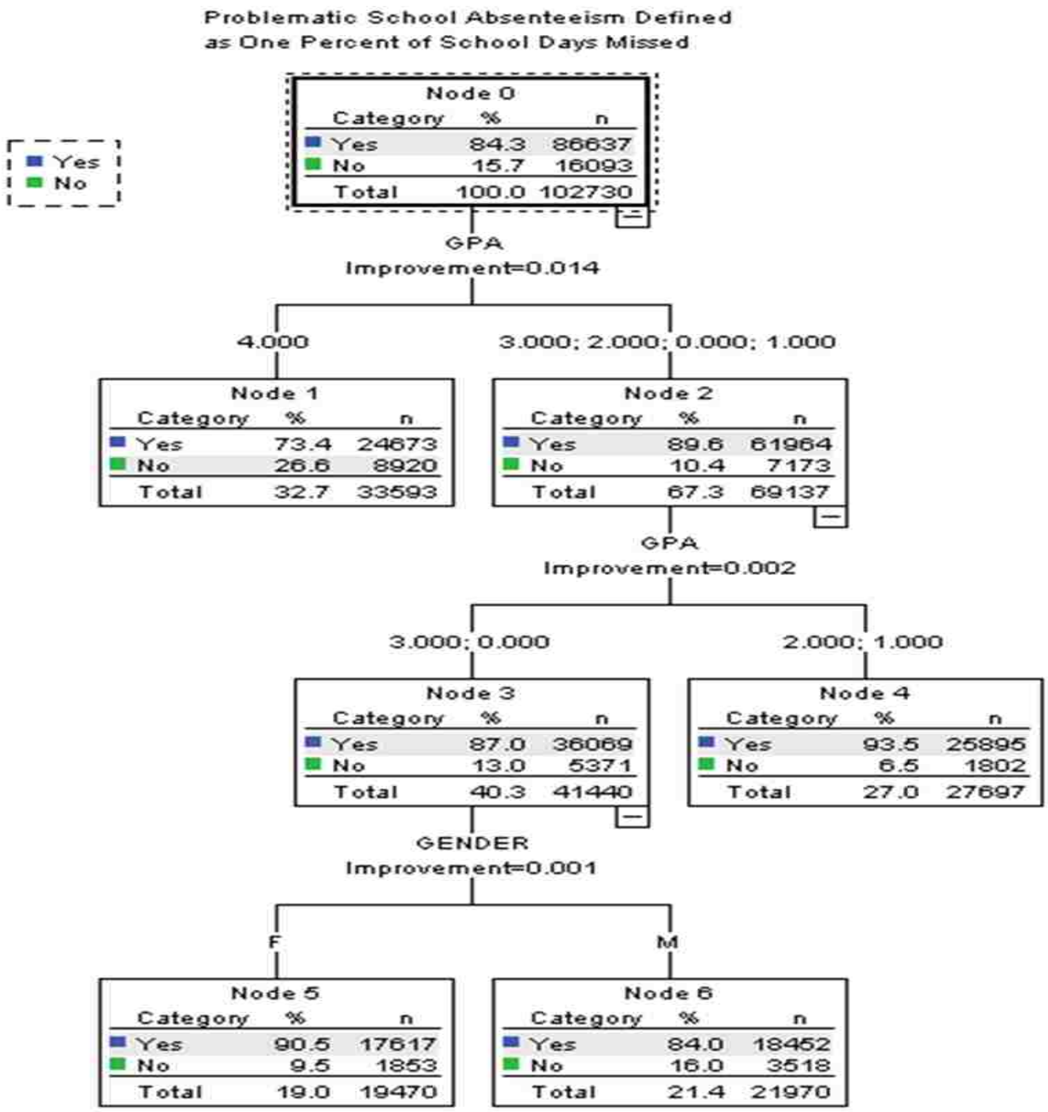

Figure 13. High school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 1% of full school days missed

The final tree-model correctly identified 69.0% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 71.5% (n = 61,964) of high school youth with problematic school absenteeism correctly (Table 22). The tree-model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 55.4% (n = 8,920) of high school

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youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (*r* = .260, *SE* = .002). The tree-model's accuracy in predicting whether a youth in high school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 74.0%.

Table 22

High School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	61,964	24,673	71.5%
No	7,173	8,920	55.4%
Overall	67.3%	32.7%	69.0%

Four subgroups associated with varying risk for problematic school absenteeism emerged. GPA was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .014). GPA split such that youth that had earned a GPA between 3.01 and 4.00 exhibited a 73.4% (*n* = 24,673) risk for problematic school absenteeism (Node 1; Terminal). However, youth that had earned a GPA between 0.00 and 3.00 or whose GPA was unknown/nonexistent were at a higher risk for exhibiting problematic school absenteeism (89.6%; *n* = 61,964; Node 2). GPA was again identified as a relevant risk factor for youth in Node 2 (Gini improvement = .002). Specifically, youth that had

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earned a GPA between 2.01 and 3.00 or whose GPA was unknown/nonexistent were less likely to exhibit problematic school absenteeism (87.0%; n = 36,069; Node 3). Conversely, youth that had earned a GPA between 0.00 and 2.00 exhibited a 93.5% (n = 25,895) risk for problematic school absenteeism (Node 4; Terminal). Gender was the next most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .001). For youth in Node 3, gender split such that being male was associated with an 84.0% (n = 18,452) risk for exhibiting problematic school absenteeism (Node 6; Terminal). However, being female placed these youth at a higher risk for exhibiting problematic school absenteeism (90.5%; n = 17,617; Node 5; Terminal).

The final tree-model thus identified two relevant risk factors (GPA and gender) that best differentiated high school youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from those with nonproblematic school absenteeism (less than 1% of full school days missed). Four subgroups of high school youth, each with varying risk for problematic school absenteeism, emerged. Youth that had earned a GPA between 0.00 and 2.00 were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding a high school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 23.

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Table 23

High School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed by Risk Probability

	If	Then
Node 1	GPA between 3.01 and 4.00	73.4% probability
Node 6	Unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND male	84.0% probability
Node 3	Unknown/nonexistent GPA or GPA between 2.01 and 3.00	87.0% probability
Node 2	Unknown/nonexistent GPA or GPA between 0.00 and 3.00	89.6% probability
Node 5	Unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND female	90.5% probability
Node 4	GPA between 0.00 and 2.00	93.5% probability

Ten Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 10% of full school days missed were obtained from base rates (i.e., "Yes" = .24, "No" = .76). Probabilities were not adjusted based on custom misclassification costs (i.e., "Yes" = 2.00, "No" = .50). The final tree-model identified three relevant risk factors that best differentiated high school youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from high school youth with nonproblematic school absenteeism (less than 10% of full school days missed): (1) GPA, (2) age, and (3) gender (Figure 14).

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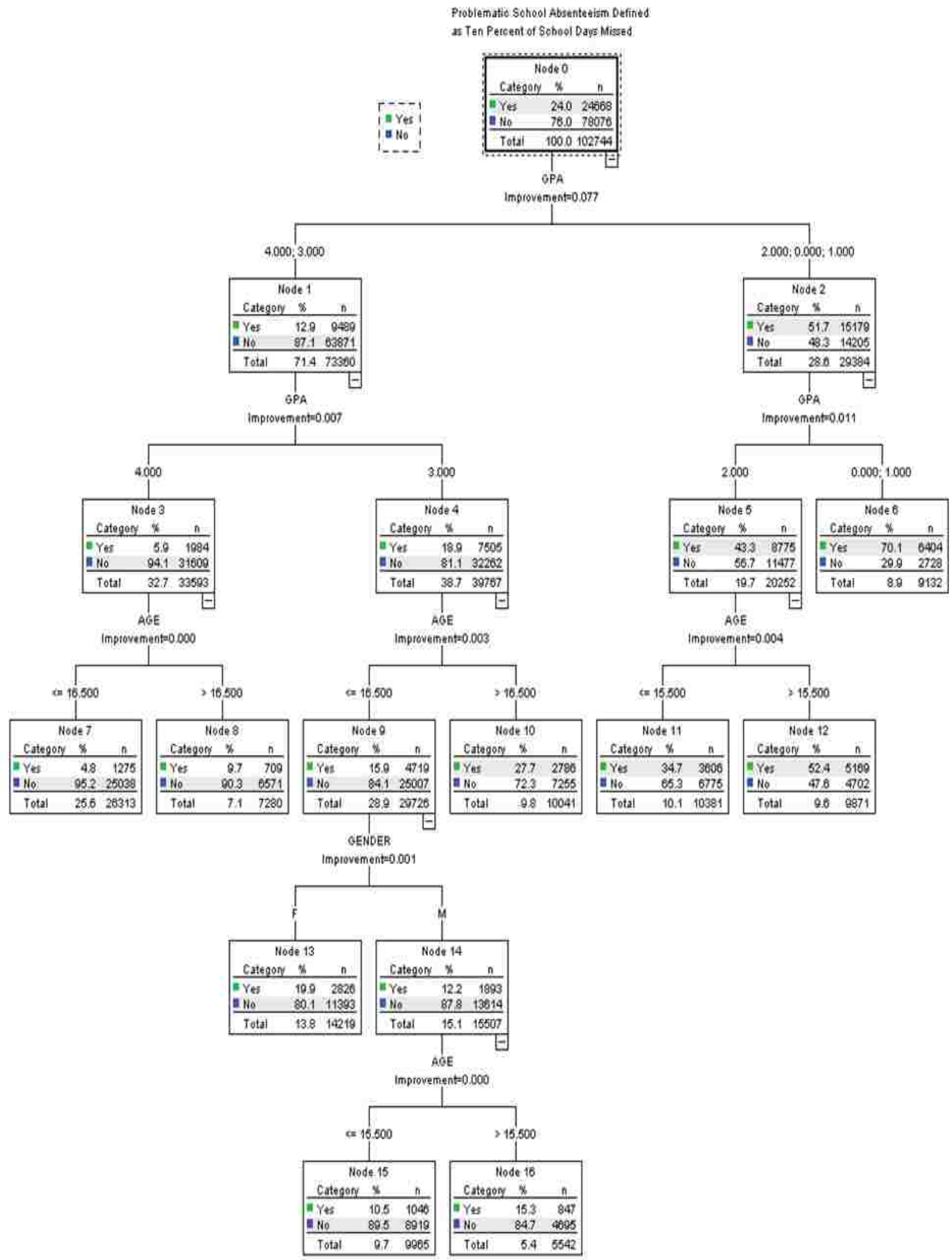

Figure 14. High school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 10% of full school days missed

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The final tree-model correctly identified 72.6% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 72.8% (*n* = 17,965) of high school youth with problematic school absenteeism correctly (Table 24). The tree-model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 72.5% (*n* = 56,616) of high school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (*r* = .236, *SE* = .002). The tree-model's accuracy in predicting whether a youth in high school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 76.4%.

Table 24

High School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	17,965	6,703	72.8%
No	21,460	56,616	72.5%
Overall	38.4%	61.6%	72.6%

Nine subgroups associated with varying risk for problematic school absenteeism emerged. GPA was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .077). GPA split such that youth that had earned a GPA between

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2.01 and 4.00 exhibited a 12.9% (*n* = 9,489) risk for problematic school absenteeism (Node 1). However, youth that had earned a GPA between 0.00 and 2.00 or whose GPA was unknown/nonexistent were at a higher risk for exhibiting problematic school absenteeism (51.7%; *n* = 15,179; Node 2). GPA was again identified as a relevant risk factor for youth in Node 2 (Gini improvement = .011). Specifically, youth that had earned a GPA between 1.01 and 2.00 were less likely to exhibit problematic school absenteeism (43.3%; *n* = 8,775; Node 5). Conversely, youth that had earned a GPA between 0.00 and 1.00 or whose GPA was unknown/nonexistent exhibited a 70.1% (*n* = 6,404) risk for problematic school absenteeism (Node 6; Terminal). Age was the next most relevant risk factor identified (Gini improvement = .004). For youth in Node 5, age split such that being age 15.5 years or younger was associated with a 34.7% (*n* = 3,606) risk for exhibiting problematic school absenteeism (Node 11; Terminal). However, being older than 15.5 years of age placed these youth at a higher risk for exhibiting problematic school absenteeism (52.4%; *n* = 5,169; Node 12; Terminal).

For youth in Node 1, GPA was again identified as a relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .007). GPA split such that earning a GPA between 3.01 and 4.00 was associated with a lower risk for exhibiting problematic school absenteeism (5.9%; *n* = 1,984; Node 3). However, earning a GPA between 2.01 and 3.00 placed these youth at an 18.9% (*n* = 7,505) risk for exhibiting problematic school absenteeism (Node 4). Age was the next most relevant risk factor identified for youth in Node 3 (Gini improvement < .001). Age split such that youth who were age 16.5 years or younger exhibited a 4.8% (*n* = 1,275) risk for problematic school

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absenteeism (Node 7; Terminal). Conversely, youth older than 16.5 years of age were at a higher risk for exhibiting problematic school absenteeism (9.7%; *n* = 709; Node 8; Terminal).

For youth in Node 4, age was also the next most relevant risk factor identified (Gini improvement = .003). Specifically, being age 16.5 years or younger was associated with a lower risk for exhibiting problematic school absenteeism (15.9%; *n* = 4,719; Node 9). Conversely, being older than 16.5 years of age placed these youth at a 27.7% (n = 2,786) risk for exhibiting problematic school absenteeism (Node 10; Terminal). Gender was the next most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .001). For youth in Node 9, gender split such that males exhibited a 12.2% (*n* = 1,893) risk for problematic school absenteeism (Node 14). Conversely, females were at a higher risk for exhibiting problematic school absenteeism (19.9%; *n* = 2,826; Node 13; Terminal). Age was again identified as a relevant risk factor for youth in Node 14 (Gini improvement < .001). Specifically, being age 15.5 years or younger was associated with a lower risk for exhibiting problematic school absenteeism (10.5%; *n* = 1,046; Node 15; Terminal). Conversely, being older than 15.5 years of age placed these youth at a 15.3% (*n* = 847) risk for exhibiting problematic school absenteeism (Node 16; Terminal).

The final tree-model thus identified three relevant risk factors (GPA, age, and gender) that best differentiated high school youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from those with nonproblematic school absenteeism (less than 10% of full school days missed). Nine subgroups of high school youth, each with varying risk for problematic school absenteeism, emerged. Youth

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that had earned a GPA between 0.00 and 1.00 or whose GPA was unknown/nonexistent were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding a high school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 25.

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Table 25

High School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed by Risk Probability

	If	Then
Node 7	GPA between 3.01 and 4.00 AND age 16.5 years or younger	4.8% probability
Node 3	GPA between 3.01 and 4.00	5.9% probability
Node 8	GPA between 3.01 and 4.00 AND older than 16.5 years of age	9.7% probability
Node 15	GPA between 2.01 and 3.00 AND male AND age 15.5 years or younger	10.5% probability
Node 14	GPA between 2.01 and 3.00 AND age 16.5 years or younger AND male	12.2% probability
Node 1	GPA between 2.01 and 4.00	12.9% probability
Node 16	GPA between 2.01 and 3.00 AND male AND older than 15.5 years of age	15.3% probability
Node 9	GPA between 2.01 and 3.00 AND age 16.5 years or younger	15.9% probability
Node 4	GPA between 2.01 and 3.00	18.9% probability
Node 13	GPA between 2.01 and 3.00 AND age 16.5 years or younger AND female	19.9% probability
Node 10	GPA between 2.01 and 3.00 AND older than 16.5 years of age	27.7% probability
Node 11	GPA between 1.01 and 2.00 AND age 15.5 years or younger	34.7% probability
Node 5	GPA between 1.01 and 2.00	43.3% probability
Node 2	Unknown/nonexistent GPA or GPA between 0.00 and 2.00	51.7% probability
Node 12	GPA between 1.01 and 2.00 AND older than 15.5 years of age	52.4% probability
Node 6	Unknown/nonexistent GPA or GPA between 0.00 and 1.00	70.1% probability

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Fifteen Percent Cutoff. Empirical prior probabilities for problematic school absenteeism defined as 15% of full school days missed were obtained from base rates (i.e., "Yes" = .15, "No" = .85). Probabilities were not adjusted based on custom misclassification costs (i.e., "Yes" = 2.50, "No" = .30). The final tree-model identified three relevant risk factors that best differentiated high school youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from high school youth with nonproblematic school absenteeism (less than 15% of full school days missed): (1) GPA, (2) age, and (3) gender (Figure 15). The final tree-model correctly identify 71.4% of all participants in the sample (i.e., those with problematic versus nonproblematic school absenteeism). The tree-model classified 82.0% (*n* = 12,879) of high school youth with problematic school absenteeism correctly (Table 26). The tree-model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 69.5% (*n* = 60,493) of high school youth with nonproblematic school absenteeism classified correctly). The cross-validated risk estimate of the overall tree-model was good (*r* = .146, *SE* = .001). The tree-model's accuracy in predicting whether a youth in high school outside this sample will exhibit problematic school absenteeism (i.e., after misclassification costs) is approximately 85.4%.

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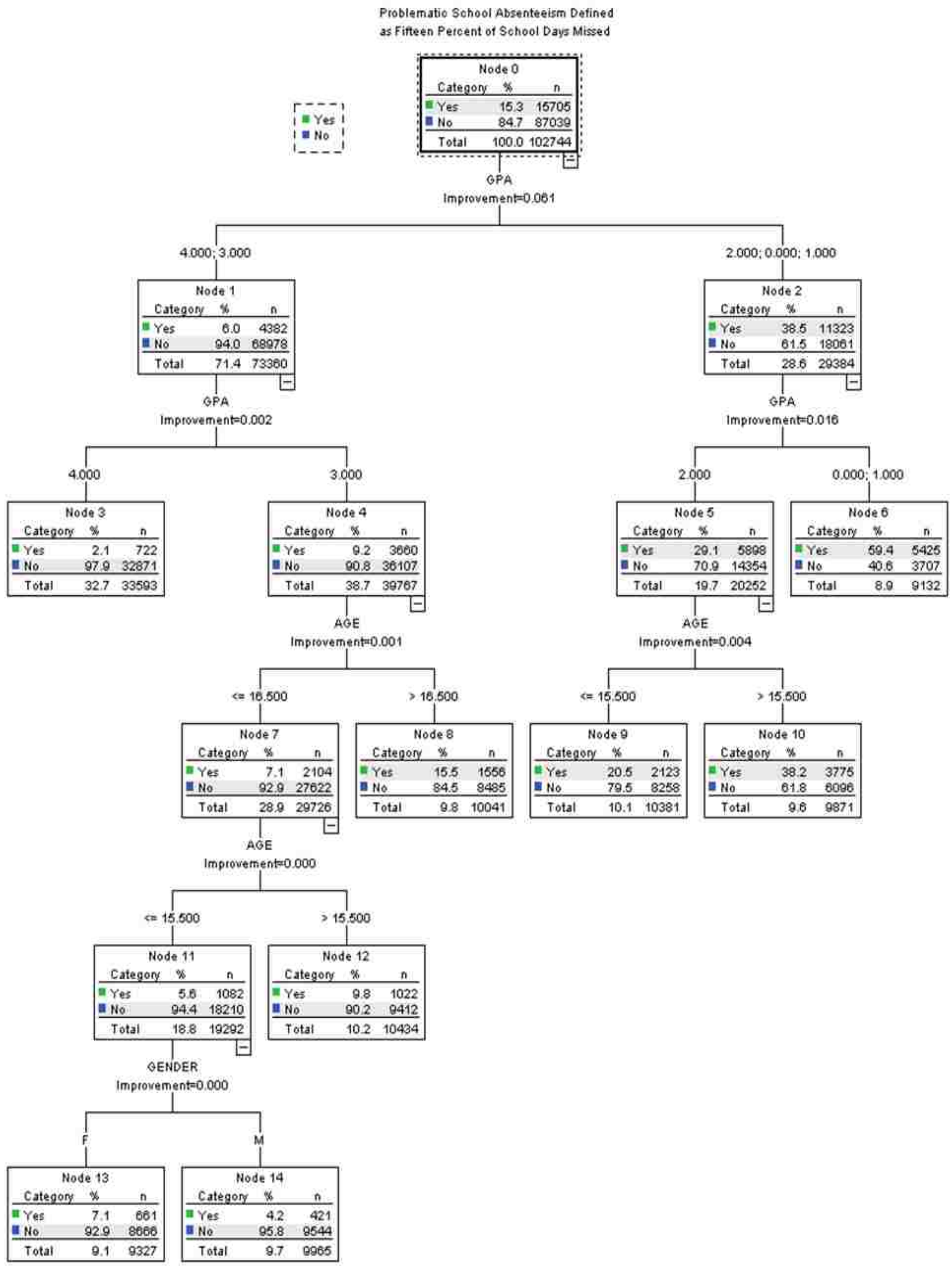

Figure 15. High school sample classification tree of risk factors for problematic school absenteeism defined as ≥ 15% of full school days missed

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Table 26

High School Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	12,879	2,826	82.0%
No	26,546	60,493	69.5%
Overall	38.4%	61.6%	71.4%

Eight subgroups associated with varying risk for problematic school absenteeism emerged. GPA was the most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .061). GPA split such that youth that had earned a GPA between 2.01 and 4.00 exhibited a 6.0% (*n* = 4,382) risk for problematic school absenteeism (Node 1). However, youth that had earned a GPA between 0.00 and 2.00 or whose GPA was unknown/nonexistent were at a higher risk for exhibiting problematic school absenteeism (38.5%; *n* = 11,323; Node 2). GPA was again identified as a relevant risk factor for youth in Node 2 (Gini improvement = .016). Specifically, earning a GPA between 1.01 and 2.00 was associated with a lower risk for exhibiting problematic school absenteeism (29.1%; *n* = 5,898; Node 5). Conversely, earning a GPA between 0.00 and 1.00 or having an unknown/nonexistent GPA placed these youth at a 59.4% (*n* = 5,425) risk for exhibiting problematic school absenteeism (Node 6; Terminal). Age was the next most relevant risk factor identified (Gini improvement = .004). For youth in Node 5, age split such that being age 15.5 years or younger was associated with a 20.5% (*n* = 2,123) risk for exhibiting problematic school absenteeism (Node 9; Terminal). However, youth

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that were older than 15.5 years of age were at a higher risk for exhibiting problematic school absenteeism (38.2%; n = 3,775; Node 10; Terminal).

For youth in Node 1, GPA was again identified as a relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement = .002). GPA split such that earning a GPA between 3.01 and 4.00 was associated with a lower risk for exhibiting problematic school absenteeism (2.1%; n = 722; Node 3; Terminal). However, earning a GPA between 2.01 and 3.00 placed these youth at a 9.2% (n = 3,660) risk for exhibiting problematic school absenteeism (Node 4). For youth in Node 4, age was the next most relevant risk factor identified (Gini improvement = .001). Age split such that youth who were age 16.5 years or younger exhibited a 7.1% (n = 2,104) risk for problematic school absenteeism (Node 7). Conversely, youth older than 16.5 years of age were at a higher risk for exhibiting problematic school absenteeism (15.5%; n = 1,556; Node 8; Terminal).

Age was again identified as a relevant risk factor for youth in Node 7 (Gini improvement < .001). Specifically, being age 15.5 years or younger was associated with a lower risk for exhibiting problematic school absenteeism (5.6%; n = 1,082). However, being older than 15.5 years of age placed these youth at a 9.8% (n = 1,022) risk for exhibiting problematic school absenteeism (Node 12; Terminal). Gender was the next most relevant risk factor for differentiating youth with problematic school absenteeism from youth with nonproblematic school absenteeism (Gini improvement < .001). For youth in Node 11, gender split such that males exhibited a 4.2% (n = 421) risk for problematic school absenteeism (Node 14; Terminal). Conversely, females were at a

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higher risk for exhibiting problematic school absenteeism (7.1%; *n* = 661; Node 13; Terminal).

The final tree-model thus identified three relevant risk factors (GPA, age, and gender) that best differentiated high school youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from those with nonproblematic school absenteeism (less than 15% of full school days missed). Eight subgroups of high school youth, each with varying risk for problematic school absenteeism, emerged. Youth that had earned a GPA between 0.00 and 1.00 or whose GPA was unknown/nonexistent were identified as the highest risk subgroup for problematic school absenteeism. The IF-THEN Rules regarding a high school youth's probability for exhibiting problematic school absenteeism based on the final tree-model are in Table 27.

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Table 27

High School Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed by Risk Probability

	IF	THEN
Node 3	GPA between 3.01 and 4.00	2.1% probability
Node 14	GPA between 2.01 and 3.00 AND age 15.5 years or younger AND male	4.2% probability
Node 11	GPA between 2.01 and 3.00 AND age 15.5 years or younger	5.6% probability
Node 1	GPA between 2.01 and 4.00	6.0% probability
Node 7	GPA between 2.01 and 3.00 AND age 16.5 years or younger	7.1% probability
Node 13	GPA between 2.01 and 3.00 AND age 15.5 years or younger AND female	7.1% probability
Node 4	GPA between 2.01 and 3.00	9.2% probability
Node 12	GPA between 2.01 and 3.00 AND older than 15.5 years of age	9.8% probability
Node 8	GPA between 2.01 and 3.00 AND older than 16.5 years of age	15.5% probability
Node 9	GPA between 1.01 and 2.00 AND age 15.5 years or younger	20.5% probability
Node 5	GPA between 1.01 and 2.00	29.1% probability
Node 10	GPA between 1.01 and 2.00 AND older than 15.5 years of age	38.2% probability
Node 2	Unknown/nonexistent GPA or GPA between 0.00 and 2.00	38.5% probability
Node 6	Unknown/nonexistent GPA or GPA between 0.00 and 1.00	59.4% probability

Other Analyses Requested by Committee

The relationships between GPA and letter grades for specific high school core academic course (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry) were investigated using Pearson product-moment

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correlation coefficient. Strong positive correlations were found for GPA and all courses (i.e., r = .545 - .720, $p < .01$). Three additional total sample classification tree-models (one for each cutoff) that excluded GPA as potential a risk factor were constructed (Appendix C). The first additional tree-model identified one relevant risk factor (ethnicity) for problematic school absenteeism defined as 1% of full school days missed. CART thus identified the same most relevant risk factor as the original output and produced an identical cross-validated risk estimate. The first additional tree-model, however, eliminated grade level and IEP eligibility as relevant risk factors. The second additional tree-model identified two relevant risk factors (age and ethnicity) for problematic school absenteeism defined as 10% of full school days missed. CART identified the same relevant risk factors as the original output. The second additional tree-model, however, was less accurate at predicting school absenteeism than the original output due to a higher cross-validated risk estimate. The third additional tree-model identified four relevant risk factors (age, ethnicity, IEP eligibility, and grade level) for problematic school absenteeism defined as 15% of full school days missed. CART identified a novel relevant risk factor from the original output (IEP eligibility). The cross-validated risk estimate of the third additional tree-model, however, was again higher than the original output. The overall predictive utilities of the three additional classification tree-models without GPA as a risk factor were limited compared to the original tree-models due to higher cross-validated risk estimates.

The relationship between age and grade level was investigated using Pearson product-moment correlation coefficient. A strong positive correlation was found between the two variables, r = .991, n = 341,892, $p < .01$. Three additional classification tree-

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models (one for each cutoff) that excluded grade level as potential a risk factor were constructed due to concerns regarding multicollinearity (Appendix C). The first additional tree-model identified three relevant risk factors (ethnicity, GPA, and age) for problematic school absenteeism defined as 1% of full school days missed. CART identified a novel relevant risk factor from the original output (age) but eliminated IEP eligibility. Conversely, both tree-models identified ethnicity and GPA as relevant risk factors. The original output and the first additional tree-model also produced identical cross-validated risk estimates. The second additional tree-model identified three relevant risk factors (GPA, age, and ethnicity) for problematic school absenteeism defined as 10% of full school days missed. CART identified the same relevant risk factors as the original output and the second additional tree-model demonstrated equal accuracy in predicting school absenteeism as well. The third additional tree-model identified three relevant risk factors (GPA, age, and ethnicity) for problematic school absenteeism defined as 15% of full school days missed. CART thus identified the same relevant risk factors as the original output and produced a nearly identical cross-validated risk estimate. The overall predictive utilities of the three additional classification tree-models without grade level as a risk factor differed minimally from the original tree-models due to the strong positive relationship between grade level and age.

Additional regression analyses were employed due to concerns regarding potential biases in the original binary tree-models. Specifically, recursive partitioning techniques select the risk factor that produces the largest reduction in the impurity value (i.e., Gini criterion) at each step in the tree-growing process. Splitting criteria emphasize a local optimum rather than a global optimum (i.e., it is a “greedy search”). Therefore, a

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direct logistic regression including previously identified relevant risk factors (age, gender, GPA, ethnicity, and IEP eligibility) was employed at each cutoff to compare overall predictive utility with original binary tree-models. Grade level, however, was not included as a potential risk factor in the analyses due to multicollinearity. Youth- and academic-related risk factors were dummy coded to align with the reference category (problematic school absenteeism; “0” = No, “1” = Yes).

One Percent. The full model contained five risk factors (Appendix D; age, gender, ethnicity, GPA, and IEP eligibility). The full model containing all of the risk factors was statistically significant, χ^2 (11, N = 101,063) = 7838.13, p < .001, indicating that the model was able to distinguish between youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) and youth with nonproblematic school absenteeism (less than 1% of full school days missed). The model as a whole explained between 7.5% (Cox and Snell R square) and 12.9% (Nagelkerke R square) of the variance in school absenteeism and correctly classified 84.5% of youth. Specifically, the model classified 99.4% (n = 84,706) of youth with problematic school absenteeism correctly. The model thus demonstrated higher sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 4.6% (n = 730) of youth with nonproblematic school absenteeism classified correctly).

Four risk factors made a unique statistically significant contribution to the model: 1) gender, ethnicity, age, and GPA. The most relevant risk factor for problematic school absenteeism was gender, recording an odds ratio of 1.663. This indicated that female youth were 1.663 times more likely to exhibit problematic school absenteeism than male youth, controlling for all other factors in the model. The odds ratio of .442 for GPA was

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less than 1, indicating that youth were .442 times less likely to exhibit problematic school absenteeism for every additional point in GPA, controlling for all other factors in the model.

Ten Percent. The full model contained five risk factors (Appendix D; age, gender, ethnicity, GPA, and IEP eligibility). The full model containing all of the risk factors was statistically significant, χ^2 (11, N = 101,064) = 24,515.332, p < .001, indicating that the model was able to distinguish between youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) and youth with nonproblematic school absenteeism (less than 10% of full school days missed). The model as a whole explained between 21.5% (Cox and Snell R square) and 32.5% (Nagelkerke R square) of the variance in school absenteeism and correctly classified 81.3% of youth. Specifically, the model classified 38.2% (n = 9,015) of youth with problematic school absenteeism correctly. The model thus demonstrated lower sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 94.5% (n = 73,197) of youth with nonproblematic school absenteeism classified correctly).

All five of the risk factors made a unique statistically significant contribution to the model. The most relevant risk factor for problematic school absenteeism was gender, recording an odds ratio of 1.812. This indicated that female youth were over 1.812 times more likely to exhibit problematic school absenteeism than male youth, controlling for all other factors in the model. The odds ratio of .249 for GPA was less than 1, indicating that youth were .249 times less likely to exhibit problematic school absenteeism for every additional point in GPA, controlling for all other factors in the model.

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Fifteen Percent. The full model contained five risk factors (Appendix D; age, gender, ethnicity, GPA, and IEP eligibility). The full model containing all of the risk factors was statistically significant, χ^2 (11, N = 101,064) = 22,479.781, p < .001, indicating that the model was able to distinguish between youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) and youth with nonproblematic school absenteeism (less than 15% of full school days missed). The model as a whole explained between 19.9% (Cox and Snell R square) and 35.3% (Nagelkerke R square) of the variance in school absenteeism and correctly classified 87.4% of youth. The model classified 30.5% (n = 4,502) of youth with problematic school absenteeism correctly. The model thus demonstrated lower sensitivity (i.e., true positive rate) than specificity (i.e., true negative rate; 97.2% (n = 83,861) of youth with nonproblematic school absenteeism classified correctly).

All five of the risk factors made a unique statistically significant contribution to the model. The most relevant risk factor for problematic school absenteeism was gender, recording an odds ratio of 1.794. This indicated that female youth were 1.794 times more likely to exhibit problematic school absenteeism than male youth, controlling for all other factors in the model. The odds ratio of .208 for GPA was less than 1, indicating that youth were .208 times less likely to exhibit problematic school absenteeism for every additional point in GPA, controlling for all other factors in the model.

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CHAPTER 5

DISCUSSION

The primary aim of the present study was to inform a multitier approach by identifying the most relevant risk factors for problematic school absenteeism using nonparametric modeling procedures. The present study examined problematic school absenteeism defined at three distinct cutoffs based on extant literature (1%, 10%, and 15% of full school days missed). The present study evaluated numerous youth- and academic-related risk factors simultaneously to determine which subgroups of youth were most likely to exhibit problematic school absenteeism at each cutoff.

Researchers have employed parametric techniques to determine potential risk factors, in isolation, for problematic school absenteeism in youth. The present study, however, is the first to use BRP procedures to identify unique patterns of risk for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed). The present study offers three classification tree-models of risk for problematic school absenteeism across a gender-balanced and ethnically diverse sample of community youth. Multiple post hoc tree-models were also constructed based on different developmental levels (i.e., elementary vs. middle vs. high school). Tree-models are briefly summarized below. Relevant risk factors are later discussed in greater detail.

Summary of Original Tree-Models

Hypothesis 1. Participation in school sports was expected to emerge as the most relevant risk factor for problematic school absenteeism, defined as equal to or greater than 1% of full school days missed. The final tree-model did not support this hypothesis

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and instead identified four relevant risk factors for differentiating youth with problematic school absenteeism (equal to or greater than 1% of full school days missed) from youth with nonproblematic school absenteeism (less than 1% of full school days missed): 1) ethnicity, 2) GPA, 3) grade level, and 4) IEP eligibility. Specifically, Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander youth exhibited higher rates of problematic school absenteeism than Asian youth. Youth with an unknown/nonexistent GPA or GPA between 0.00 and 2.00 were also at a greater risk for problematic school absenteeism than youth that had earned a GPA between 2.01 and 4.00. Youth in the 1st, 2nd, 9th, 10th, 11th, and 12th grade displayed higher rates of problematic school absenteeism than youth in all other grades. Youth that were eligible to receive an IEP during the 2015-16 academic year were also at a greater risk for problematic school absenteeism than youth that were not eligible to receive an IEP. The highest risk subgroup for problematic school absenteeism defined as 1% of full school days missed was youth of Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander ethnicity with an unknown/nonexistent GPA or GPA between 0.00 and 2.00 in the 1st, 2nd, 9th, 10th, 11th, or 12th grade.

Hypothesis 2. Grade level, letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry), and GPA were expected to emerge as the most relevant risk factors for problematic school absenteeism, defined as equal to or greater than 10% of full school days missed. The final tree-model partially supported this hypothesis and identified three relevant risk factors for differentiating youth with problematic school absenteeism (equal to or greater than 10% of full school days missed) from youth with

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nonproblematic school absenteeism (less than 10% of full school days missed): 1) GPA, 2) age, and 3) ethnicity. Specifically, youth with a GPA between 0.00 and 2.00 exhibited higher rates of problematic school absenteeism than youth with an unknown/nonexistent GPA or GPA between 2.01 and 4.00. Youth aged 15.5 years of older were also at a greater risk for problematic school absenteeism than youth younger than 15.5 years of age. African American and American Indian youth exhibited higher rates of problematic school absenteeism than all other youth as well. The highest risk subgroup for problematic school absenteeism defined as 10% of full school days missed was youth that had earned a GPA between 0.00 and 2.00.

Hypothesis 3. Age, gender, and ethnicity were expected to emerge as the most relevant risk factors for problematic school absenteeism, defined as equal to or greater than 15% of full school days missed. The final tree-model partially supported this hypothesis and identified four relevant risk factors for differentiating youth with problematic school absenteeism (equal to or greater than 15% of full school days missed) from youth with nonproblematic school absenteeism (less than 15% of full school days missed): 1) GPA, 2) age, 3) ethnicity, and 4) grade level. Specifically, youth with a GPA between 0.00 and 2.00 exhibited higher rates of problematic school absenteeism than youth with an unknown/nonexistent GPA or GPA between 2.01 and 4.00. Youth aged 16.5 years or older were also at a greater risk for problematic school absenteeism than youth younger than 16.5 years of age. African American and American Indian youth exhibited higher rates of problematic school absenteeism than all other youth. Youth in the 1st, 6th, 7th, 8th, 10th, 11th, or 12th grade also exhibited higher rates of problematic school absenteeism than youth in all other grades. The highest risk subgroup for

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problematic school absenteeism defined as 15% of full school days missed was youth that had earned a GPA between 0.00 and 2.00.

Summary of Post Hoc Analyses

CART was employed at different developmental levels (i.e., elementary vs. middle vs. high school). Specifically, three classification tree-models were constructed for each developmental level, one to represent each of the distinct cutoffs for problematic school absenteeism (1%, 10%, and 15% of full school days missed). The present study examined whether the most relevant risk factors identified at each cut off differed based on a youth's developmental level. Risk factors commonly identified within the tree-models are outlined below.

Elementary School Youth. Ethnicity, grade level, and IEP eligibility emerged as consistent relevant risk factors for differentiating elementary school youth with problematic school absenteeism from elementary school youth with nonproblematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, African American and American Indian youth regularly exhibited higher rates of problematic school absenteeism than all other youth. Elementary school youth in the 1st or 2nd grade also consistently exhibited higher rates of problematic school absenteeism than elementary school youth in the 3rd, 4th, or 5th grade. Elementary school youth that were eligible to receive an IEP during the 2015-2016 academic year were repeatedly more likely to exhibit problematic school absenteeism than elementary school youth that were not eligible to receive an IEP as well. The highest risk subgroup for problematic school absenteeism defined as 1% of full school days missed was elementary school youth of Hispanic, African American, Caucasian, Biracial, American

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Indian, or Pacific Islander ethnicity in the 1st or 2nd grade. Elementary school youth of African American or American Indian ethnicity in the 1st or 2nd grade were identified as the highest risk subgroup for problematic school absenteeism defined as both 10% and 15% of full school days missed.

Middle School Youth. Ethnicity and IEP eligibility emerged as consistent relevant risk factors for differentiating middle school youth with problematic school absenteeism from middle school youth with nonproblematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, Hispanic, African American, Caucasian, Biracial, Pacific Islander, and American Indian middle school youth regularly exhibited higher rates of problematic school absenteeism than Asian middle school youth. Middle school youth that were eligible to receive an IEP during the 2015-2016 academic year were repeatedly more likely to exhibit problematic school absenteeism than middle school youth that were not eligible to receive an IEP as well. The highest risk subgroup for problematic school absenteeism defined as 1% of full school days missed was middle school youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, and American Indian ethnicity that were eligible to receive an IEP during the 2015-16 academic year. The highest risk subgroup for problematic school absenteeism defined both as 10% and 15% of full school days missed was middle school youth of Hispanic, African American, Caucasian, Biracial, Pacific Islander, and American Indian ethnicity.

High School Youth. GPA, gender, and age emerged as consistent relevant risk factors for differentiating high school youth with problematic school absenteeism from high school youth with nonproblematic school absenteeism among the three distinct

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cutoffs (1%, 10%, and 15% of full school days missed). Specifically, high school youth that had earned a GPA between 0.00 and 2.00 or whose GPA was unknown/nonexistent exhibited higher rates of problematic school absenteeism than high school youth with a GPA between 2.01 and 4.00. Female high school youth also consistently exhibited higher rates of problematic school absenteeism than male high school youth. Youth that were age 15.5 years or older repeatedly exhibited higher rates of problematic school absenteeism than youth younger than 15.5 years of age as well. The highest risk subgroup for problematic school absenteeism defined as 1% of full school days missed was high school youth that had earned a GPA between 0.00 and 2.00. The highest risk subgroup for problematic school absenteeism defined both as 10% and 15% of full school days missed was high school youth with an unknown/nonexistent GPA or GPA between 0.00 and 1.00.

Summary of Other Analyses Requested by Committee

Additional classification tree-models were also constructed due to concerns regarding multicollinearity between GPA and letter grades for specific high school academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry). Specifically, CART was employed at the three distinct cutoffs (1%, 10%, and 15% of full school days missed) without GPA included as a potential risk factor. The overall predictive utilities of the three additional classification tree-modes without GPA as a risk factor were limited compared to the original total sample tree-models due to higher cross-validated risk estimates.

Additional classification tree-models were also constructed due to concerns regarding multicollinearity between age and grade level. Specifically, CART was

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employed at the three distinct cutoffs (1%, 10%, and 15% of full school days missed) without grade level included as a potential risk factor as a result of its significant positive relationship with age. The overall predictive utilities of the three additional classification tree-models without grade level as a risk factor differed minimally from the original total sample tree-models due to the strong positive relationship between grade level and age.

Additional regression analyses were also employed due to concerns regarding potential biases in the original binary tree-models. Specifically, a direct logistic regression including previously identified relevant risk factors (age, gender, GPA, ethnicity, and IEP eligibility) was employed at the three distinct cutoffs. Results indicated that the original binary tree-models explained more variance in the prediction of problematic school absenteeism than the regression models, as expected.

Relevant Risk Factors

The present study aimed to inform a multitier approach for problematic school absenteeism by constructing classification tree-models to determine the most relevant risk factors for problematic school absenteeism defined at three distinct cutoffs (1%, 10%, and 15% of full school days missed) among youth at different developmental levels (i.e., elementary school, middle school, and high school). Six risk factors were consistently identified as relevant among the models: 1) age, 2) ethnicity, 3) gender, 4) GPA, 5) grade level, and 6) IEP eligibility. The possible mechanisms underlying these risk factors are discussed next.

Age. Classification tree-models consistently identified age as a relevant risk factor for problematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, youth older than 16 years of age regularly

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exhibited higher rates of problematic school absenteeism than youth aged 15-16 years who, in turn, exhibited higher rates of problematic school absenteeism than youth younger than 15 years of age (often within the context of a lower GPA and a minority ethnicity). Findings from the present study align with previous research that has established a relationship between a youth's age and school absenteeism (Hansen et al., 1998; Kleine, 1994; NCES, 2011). For example, school absences tend to become more severe as a youth ages. Numerous studies have demonstrated that school absenteeism often peaks around 14-15 years of age (Haight et al., 2011; Kearney & Albano, 2007; Last & Strauss, 1990; McShane et al., 2001; Ollendick & Mayer, 1984; Walter et al., 2010). Many older youth may miss school to care for younger family members or become parents themselves and to obtain employment (Bridgeland, DiIulio, & Morison, 2006; Kearney, 2007; Kearney 2008b).

Ethnicity. Classification tree-models consistently identified ethnicity as a relevant risk factor for problematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, African American and American Indian youth repeatedly demonstrated higher rates of problematic school absenteeism than all other youth (often within the context of a lower GPA and older age). Asian youth, however, regularly exhibited the lowest rates of problematic school absenteeism. Results from the present study align with previous studies that have found a relationship between ethnic minorities and school absenteeism (APA, 2013; NCES, 2015; Virtanen et al., 2014). Absenteeism rates tend to be higher among ethnic minorities, such as African American and American Indian youth, especially in community settings (Kearney, 2001; Kearney, 2006b; NCES, 2011; NCES, 2016b). Problematic school

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absenteeism in African American youth may be associated with lower socioeconomic status and poor neighborhood conditions as well as a lack of parental involvement and behavioral control (Bean, Barber, & Crane, 2006; Jeynes, 2005; Noguera, 2003; Vartanean & Gleason, 1999). Reasons for educational failure and school dropout among American Indian youth may include a lack of language proficiency and cross-cultural teaching strategies, incongruence between culture of the school and culture of the Native community, poor parental involvement in the design and implementation of school programs, and feelings of isolation (Barnhardt, 1990; Freeman & Fox, 2005; Larimore, 2000; Stiles, 1997; Tippeconnic & Faircloth, 2010). Asian youth, on the other hand, rarely miss school and are often considered "model minorities" due to high educational aspirations (Kao, 1995; Kao & Tienda, 1998). The success of Asian youth may be attributed to family expectations and cultural values (Hsin & Xie, 2014; Kwong & Lee, 1998).

Gender. Classification tree-models consistently identified gender as a relevant risk factor for problematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, female youth repeatedly demonstrated higher rates of problematic school absenteeism than male youth (often within the context of a lower GPA and older age). Findings conflict with previous research that demonstrates a relationship between male gender and the severity of school absences (Corville-Smith et al., 1998; McCoy et al., 2007; Wagner et al., 2004). One reason for this discrepancy may be the unexpected interaction between female gender and lower academic performance within the tree-models. For example, several studies have found significant gender differences in educational attainment such that females often

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outperform males (Cole, 1997; Duckworth & Seligman, 2006). This difference in performance has been attributed to the ability to self-regulate which includes paying attention, following rules, resisting temptation, and inhibiting inappropriate actions (Duckworth & Seligman, 2005; McClelland et al., 2007; Suchodoletz, Trommsdorff, Heikamp, Wieber, & Gollwitzer, 2009).

GPA. Classification tree-models consistently identified GPA as a relevant risk factor for problematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, youth that had earned a GPA between 0.00 and 2.00 repeatedly exhibited higher rates of problematic school absenteeism than youth that had earned a GPA between 2.01 and 4.00 (often within the context of older age and a minority ethnicity). Earning a GPA of 2.00 or below is equivalent to receiving an average of C letter grades or worse. Results align with studies that have found a relationship between poor academic performance and school absenteeism *(*Dreyfoos, 1990; Finn, 1993; Gottfried, 2009; Lehr et al., 2004; Steward et al., 2008). The exact nature of this relationship may be circular, however. For example, poor class performance may result in a lack of motivation to attend school. Yet, missing class often leads to incomplete assignments and a reduction in grades. The present study did not find letter grades for specific high school core academic courses (i.e., Algebra I, Algebra II, Biology, Chemistry, English 9, English 10, English 11, English 12, and Geometry) to be a relevant risk factor for problematic school absenteeism at any of the distinct cutoffs, despite the inherent relationship between course grades and GPA. Findings from the present study may have been affected by missing data for course grades. Regardless, the saliency of

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GPA as a risk factor for problematic school absenteeism has practical implications for clinicians and educators and cannot be ignored.

Grade Level. Classification tree-models consistently identified grade level as a relevant risk factor for problematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, youth in the 1st or 2nd grade repeatedly exhibited higher rates of school absenteeism than youth in other grades (within the context of a minority ethnicity and eligibility for an IEP). Findings from the present study align with previous research that demonstrates a relationship between early school years and school absenteeism (Elliot, 1999; King & Bernstein, 2001; King et al., 2001). For example, youth entering a school building for the first time, such as those in 1st grade, are at a greater risk for more severe absences (Kearney & Albano, 2000).

Youth in middle school (6th, 7th, or 8th grade) also repeatedly exhibited higher rates of school absenteeism than youth in other grades (often within the context of a minority ethnicity and eligibility for an IEP). Findings from the present study support extant literature that indicates a relationship between middle school and the severity of school absences (Balfanz & Byrnes, 2012; King & Bernstein, 2001). The transition into secondary school is likely to result in peaks of school absenteeism due to adjustment difficulties, peer harassment, and increases in school violence and disciplinary actions such as suspensions (Balfanz et al., 2007; Juvonen, Nishina, & Graham, 2000; Ramirez et al., 2012; Rumberger, 1995).

Youth in the later years of high school (10th, 11th, or 12th grade) repeatedly exhibited higher rates of school absenteeism than other youth as well (often within the context of a lower GPA, a minority ethnicity, and eligibility for an IEP). Findings from

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the present study align with previous research that demonstrates a relationship between high school and school absenteeism (NCES, 2016a; Utah Education Policy Center, 2012). The severity of a youth's school absences often worsens as he or she progresses though secondary school. School absenteeism often reaches its peak in 12^{th} grade (Balfanz & Byrnes, 2012). Reasons for this progression are varied but may include a reduction in parental involvement and poor communication between parents and teachers as well as an increase in youth independence and job opportunities (Bridgeland et al, 2006; Kearney & Silverman, 1995).

IEP Eligibility. Classification tree-models consistently identified IEP eligibility as a relevant risk factor for problematic school absenteeism among the three distinct cutoffs (1%, 10%, and 15% of full school days missed). Specifically, youth that were eligible to receive an IEP during the 2015-16 academic year repeatedly exhibited higher rates of problematic school absenteeism than youth that were not eligible to receive an IEP (often within the context of a minority ethnicity and a grade level of 1 or 2). Results align with studies that have found a relationship between learning problems in youth and the severity of school absences (Naylor et al., 1994; Reid, 1984). For example, youth with low academic self-concepts and learning problems in math, reading, and written language are often at a greater risk for exhibiting school absenteeism (Ginsburg, Jordan, & Chang, 2014; Monk & Ibrahim, 1984). Youth with learning problems may miss school due to concurrent behavioral problems and placement in pullout special education programs as well as feelings of frustration and discouragement, among others (Murray, Goldstein, Nourse, & Edgar, 2000; Winters, 1997).

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Clinical Implications

The present study has implications for a concrete distinction between Tier 1 (preventative) and Tier 2 (targeted) in the MTSS model. Specifically, findings suggest that 1% and 15% of full school days missed may not be useful cutoffs, resulting in 10% as the best demarcation point for problematic school absenteeism. Base rates of youth attendance suggest that 1% of full school days missed may not be a practical cutoff for problematic school absenteeism. The present study demonstrated that 85.2%, 16.3%, and 8.6% of youth exhibited problematic school absenteeism defined as 1%, 10%, and 15% of full school days missed, respectively. According to these definitions, enforcing a 1% cutoff would identify more than three-quarters of the student population as exhibiting a problem with school attendance. MTSS indicates that resources for the remediation of school absences would then need to be implemented with all of these students. Tier 2 assessment strategies include youth and parent interviews, questionnaires, behavioral observations, academic record review, and formal testing. Tier 2 intervention strategies involve multidisciplinary efforts to improve a youth's psychological functioning and re-engagement with school such as increased parent involvement, teacher and peer mentoring, and psychotherapy, among others (Kearney & Graczyk, 2014). Problematic school absenteeism defined as 1% of full school days missed would thus prove inefficient and costly.

Risk factors identified within the tree-models also suggests that 15% of full school days missed may not be an appropriate cutoff for problematic school absenteeism. Tree-models for 10% and 15% of full school days missed differed minimally with respect to the identified relevant risk factors and highest risk subgroups, even at different

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developmental levels. For example, the total sample tree-models for 10% and 15% of full school days missed were the only models that differed and it was only with respect to one relevant risk factor (i.e., grade level). The difference between 10% and 15% of full school days missed may thus not be a meaningful distinction and waiting until a youth exhibits 15% of full school days missed may not align with early identification and intervention components necessary for successful remediation.

The present study also has implications for the assessment of youth at highest risk for problematic school absenteeism. Numerous factors have been identified in the extant literature as heightening a youth's risk for problematic school absenteeism. The present study, however, provides preliminary support for the idea that certain youth- and academic-related risk factors may be more relevant than others. Specifically, a youth's age, ethnicity, gender, GPA, grade level, and IEP eligibility may be the most relevant risk factors to consider as absenteeism becomes more severe from Tier 1 to Tier 2 in the MTSS model. An understanding of which risk factors are most relevant for problematic school absenteeism helps researchers, clinicians, and educators determine optimal assessment methods. Specific assessment methods are discussed next in detail.

Tier 1 Assessment. Tier 1 strategies, or universal assessment and intervention, address all youth regardless of their attendance. These universal strategies are intended to focus on the prevention of school absenteeism at a broad level and often involve school-wide or district-wide approaches (Kearney, 2016). A successful Tier 1 approach will include a proactive assessment component with multiple targets to aid in the identification of youth at risk for attendance problems (Kearney, 2016). Actual absences from school are the clearest indication of problematic absenteeism. The primary target of

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Tier 1 assessment is thus daily record keeping of youth absences, both excused and unexcused. Schools should collect data regarding both the frequency and duration of youth absences such as tardiness, missed class periods, and the number of full school days absent (Kearney & Graczyk, 2014). School administrators and personnel should frequently examine youth attendance records. No blueprint exists for how often absenteeism data should be evaluated, however, researchers recommend that a thorough review be completed at least twice per month (Kearney & Graczyk, 2014; Mac Iver & Mac Iver, 2010).

Tier 1 assessment may also involve categorizing attendance data during the review process to improve its effectiveness. The present study suggests that youth absences may be categorized by demographic and academic factors (i.e., age, ethnicity, gender, GPA grade level, and IEP eligibility). Absentee rates may then be calculated for high risk subgroups of youth. For example, educators should closely monitor a youth's age, as older youth tend to exhibit more severe absences than younger youth. The present study demonstrated that youth older than 16 years of age are at a greater risk for problematic school absenteeism than youth aged 15-16 years who, in turn, are at a greater risk for problematic school absenteeism than youth younger than 15 years of age (often within the context of a lower GPA and a minority ethnicity).

Educators should pay special attention to a youth's ethnicity as well because minority youth tend to exhibit more severe absences than White youth. Findings from the present study suggest African American and American Indian youth may be at the highest risk for problematic school absenteeism (often within the context of a lower GPA and older age). Higher rates of school nonattendance among minority youth may reflect

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feelings of disconnect and isolation (Tippeconnic & Faircloth, 2010). Therefore, Tier 1 assessment may also involve surveying youth about school climate or the general quality of school life. Aspects of school climate related to problematic school absenteeism include unsafe school environment, boredom, uninteresting classes, inadequate peer and teacher support, and inconsistent rules (Bridgeland et al., 2006).

Educators should also closely consider a youth's gender, as differences often exist with respect to the severity of school absences. Findings from the present study, however, contradict extant literature and suggest that female youth are at a greater risk for problematic school absenteeism than male youth (often within the context of a lower GPA and older age). This discrepancy may be due to the unexpected interaction between female gender and lower academic performance. Educators should thus pay special attention to a youth's academic record as well. The present study demonstrated that youth with a GPA between 0.00 and 2.00 (i.e., an average of C letter grades or worse) may be at the highest risk for problematic school absenteeism (often within the context of older age and a minority ethnicity).

Educators should also closely monitor the grade level of a youth, as beginning school for the first time and progressing through the latter years of secondary school is often associated with higher rates of school nonattendance. Findings from the present study suggest that youth in 1st or 2nd grade may be at the highest risk for problematic school absenteeism as well as youth in 9th, 10th, 11th, and 12th grade. Educators should pay special attention to youth with learning problems as well because youth with deficits in math, reading, and writing often exhibit severe absences. The present study demonstrated that youth that were eligible to receive an IEP during the 2015-16 academic

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year were at a greater risk for problematic school absenteeism than youth that were not eligible to receive an IEP. Tier 1 assessment may thus include routine academic screening for deficits in learning to address school absenteeism (Kearney, 2016).

The aforementioned assessment strategies may be utilized regardless of which cutoff for problematic school absenteeism a school system decides to implement. The present study suggests that 10% of full school days missed may be the best demarcation point for problematic school absenteeism, however. Some youth will inevitably reach this clinical cutoff and move from Tier 1 to Tier 2 in the MTSS model, despite school administrators' best efforts to monitor absences and related risk factors. Youth that transition to Tier 2 exhibit problematic school absenteeism and have reached a predetermined cutoff. A more comprehensive set of assessment strategies should be implemented at this point to address these emerging cases of problematic school absenteeism.

Limitations

Findings from the present study should be considered with caution due to various limitations. First, this study relied on data present in youth education records monitored by each school within the Clark County School District. Data were collected in accordance with FERPA guidelines and thus the present study only had access to those variables available for disclosure (i.e., demographic and academic information). A second limitation is the reliability of the data. Demographic information is provided by youth and/or their caregivers and may have been impacted by forgetfulness, response distortion, or failure to communicate. Additionally, multiple school administrators and personnel are responsible for monitoring and entering academic information into a

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youth's education record. Data may have been impacted by diligence in record-keeping (Heckman & LoFontaine, 2010; Orfield, 2006). Results are thus subject to participant bias.

Third, generalizability of the findings from the present study may be limited. Although the Clark County School District represents a diverse community, the present study utilized a convenience sample and thus application to different settings and populations is unclear. The present study also produced some tree-models with higher risk estimates than anticipated. The overall quality of these tree-models remained adequate but findings may not be relevant to other populations. Furthermore, the present study utilized a dichotomous dependent variable (i.e., 1%, 10%, and 15% cutoff for problematic school absenteeism) which may have biased the results. Post hoc analyses, however, revealed the classification tree-models to be superior to logistic regression models.

Recommendations for Future Research

Future research evaluating youth at heightened risk for problematic school absenteeism should address these limitations. Researchers should strive to obtain access to additional information monitored by school systems that may be potential risk factors. The present study only examined youth- and academic-related risk factors but there are many contextual variables that may enhance risk for school absenteeism. For example, researches may evaluate social factors by examining unsatisfactory behavior marks or office disciplinary referrals such as suspensions and expulsions. Youth with referred for disruptive or aggressive behavior may have coping deficits along with internalizing and externalizing behavior problems that are often predictive of attendance problems (Ingul et

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al., 2012; Kearney & Albano, 2004; McShane et al., 2001). On the other hand, researchers should also explore variables that may be associated with higher rates school attendance such as family involvement (Hill & Tyson, 2009) and teacher and peer relationships (Way, Reddy, & Rhodes, 2007). Consideration of risk and protective factors may provide researchers, clinicians, and educators with valuable information about patterns of school absenteeism and better inform assessment and prevention practices for this population.

Researchers should continue to study risk factors for problematic school absenteeism utilizing diverse samples, especially in community settings. Youth with attendance problems represent an extremely heterogeneous population across domains such as age, ethnicity, and socioeconomic status. Clinical settings, however, tend to assess and treat absentee youth who are predominantly white and from families with higher socioeconomic status (Bernstein & Borchardt, 1996; Hansen et al., 1998; Kearney, 2007). Studies that utilize homogeneous samples will likely produce results with very limited generalizability. Additionally, research that examines the role of ethnic identity is needed. The present study evaluated general ethnic status and found that African American and American Indian youth were routinely at a greater risk for exhibiting problematic school absenteeism than White, Hispanic, Pacific Islander, Biracial, and Asian youth. The disparate nature of these findings emphasizes the importance of assessing cultural values and beliefs as potential risk factors for school absenteeism.

Additional studies on the interactive role of risk factors for problematic school absenteeism are needed. Researchers should reduce efforts to identify variables related to overall school absences, as preliminary results suggest that distinct cutoffs of problematic

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school absenteeism are associated with varying risk factors. The mechanisms underlying the intricate relationships between specific risk factors and problematic school absenteeism observed in the present study should be explored further. Parametric techniques may be utilized to examine why certain risk factors emerged as relevant for one distinct cutoff of problematic school absenteeism but not another. A better understanding of the dynamics involved in supporting and maintaining the observed relationships may enable researchers, clinicians, and educators to more accurately identify highest risk youth and further improve prevention and assessment practices for this population.

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Appendix A

CCSD IRB Approval Letter

ASSESSMENT, ACCOUNTABILITY, RESEARCH,
AND SCHOOL IMPROVEMENT

4212 Eucalyptus Avenue • Las Vegas, Nevada 89121 • (702) 799-1041 • FAX (702) 799-5067

CCSD
CLARK COUNTY
SCHOOL DISTRICT

BOARD OF SCHOOL TRUSTEES

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Carolyn Edwards, Member
Deanna L. Wright, Member

Pat Skorkowsky, Superintendent

April 10, 2017

Kyleigh K. Sheldon, M.A.
2904 Currant Lane
Henderson, NV 89074

Dear Kyleigh:

The Research Review Committee of the Clark County School District has reviewed your requested extension to the project entitled: *Risk Factors of Problematic School Absenteeism & Application #77.* The committee is pleased to inform you that your proposal has been approved with the following provisos:

1. No changes to the protocol on file for Research Application #77.
2. No research will be conducted within CCSD schools/facilities.
3. No human participant(s) are required for this research project.
4. Provide a copy of your research findings and results.

This research protocol is approved for a period of one year from the approval date. The expiration of this protocol is 4/10/2018. You must provide a letter requesting an extension *one month* prior to the expiration date. The letter must indicate whether there will be any modifications to the original protocol. If there is any change to the protocol it will be necessary to request additional approval for such change(s) in writing through the Research Review Committee.

Please provide a copy of your research findings to this office upon completion. We look forward to the results. If you have any questions or require assistance please do not hesitate to contact this office at (702) 799-1041 Ext. 5269 or e-mail at kretzl@interact.ccsd.net.

Sincerely,

Kenneth Retzl
Coordinator III
Department of Accountability & Research
Co-Chair, Research Review Committee

Main Office: 5100 WEST SAHARA AVENUE • LAS VEGAS, NEVADA 89146 • TELEPHONE (702) 799-5000

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Appendix B

UNLV IRB Approval Letter

UNLV

UNLV Social/Behavioral IRB - Administrative Review Notice of Excluded Activity

DATE:	January 27, 2016
TO:	Christopher Kearney
FROM:	UNLV Social/Behavioral IRB
PROTOCOL TITLE:	[852383-1] Identifying Youth at High Risk for Problematic School Absenteeism Using Nonparametric Modeling
SUBMISSION TYPE:	New Project
ACTION:	EXCLUDED - NOT **HUMAN SUBJECTS** RESEARCH
REVIEW DATE:	January 27, 2016
REVIEW TYPE:	Administrative Review

Thank you for your submission of New Project materials for this protocol. This memorandum is notification that the protocol referenced above has been reviewed as indicated in Federal regulatory statutes 45CFR46.

The UNLV Social/Behavioral IRB has determined this protocol does not meet the definition of human subjects research under the purview of the IRB according to federal regulations. It is not in need of further review or approval by the IRB.

We will retain a copy of this correspondence with our records.

Any changes to the excluded activity may cause this protocol to require a different level of IRB review. Should any changes need to be made, please submit a Modification Form.

If you have questions, please contact the Office of Research Integrity - Human Subjects at IRB@unlv.edu or call 702-895-2794. Please include your protocol title and IRBNet ID in all correspondence.

Office of Research Integrity - Human Subjects
4505 Maryland Parkway . Box 451047 . Las Vegas, Nevada 89154-1047 (702) 895-2794 . FAX: (702) 895-0805 . IRB@unlv.edu

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APPENDIX C

Tables and Figures for Committee Requested CART Analyses

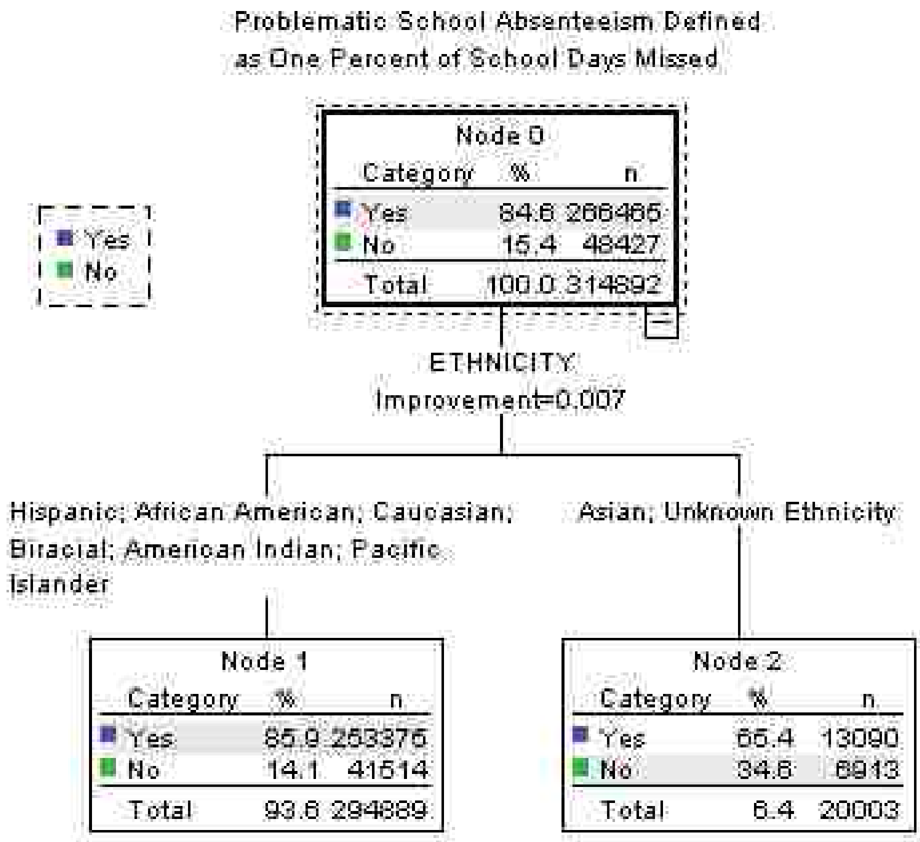

Figure C1. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 1% of full school days missed without GPA

Table C1

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed without GPA

Problematic School	Predicted		Percent Correct
Absenteeism	*Yes*	*No*	
Yes	253,375	13,090	95.1%
No	41,514	6,913	14.3%
Overall	93.6%	6.4%	82.7%

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Table C2

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed without GPA

	IF	THEN
Node 2	Asian or UnknownEthnicity	65.4% probability
Node 1	Hispanic, African American, Caucasian, Biracial, American Indian, or Pacific Islander	85.9% probability

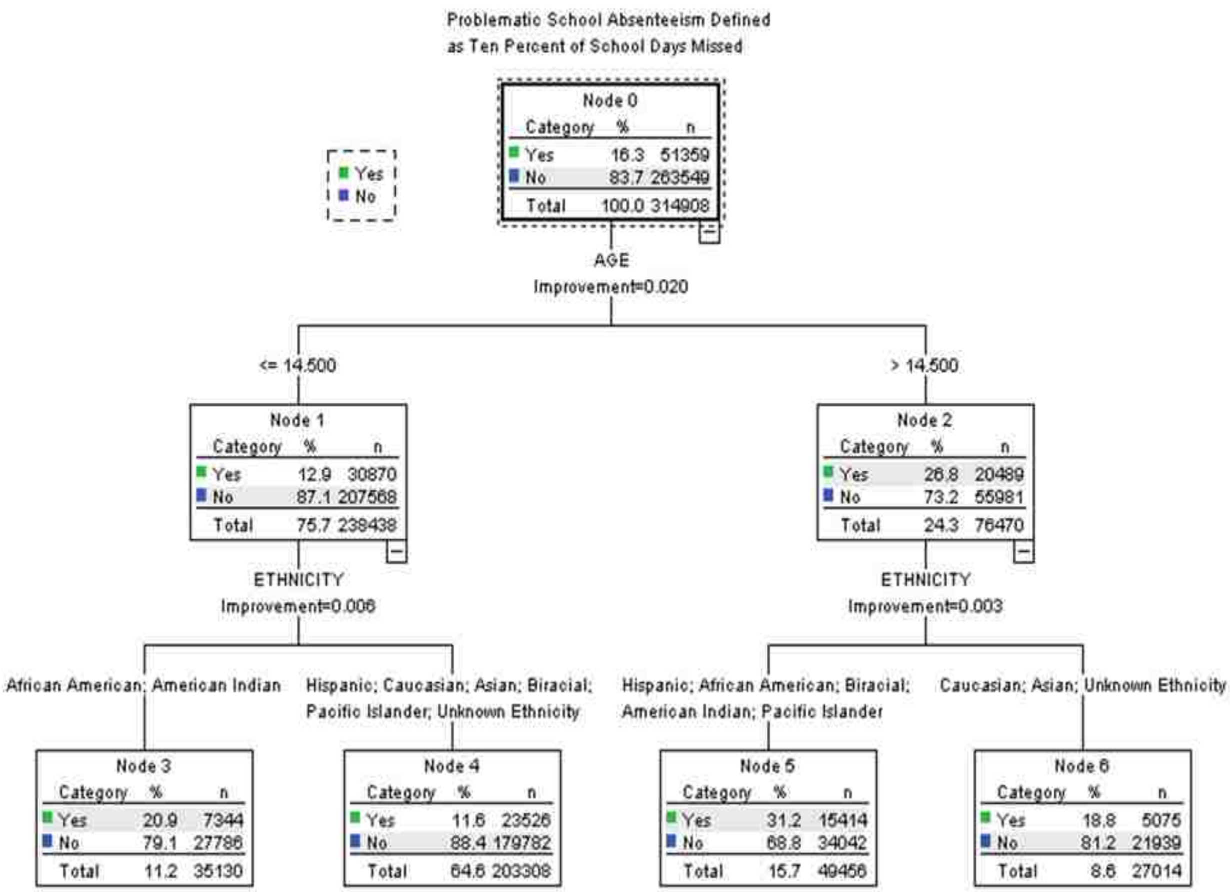

Figure C2. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 10% of full school days missed without GPA

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Table C3

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed without GPA

Problematic School Absenteeism	Predicted Yes	Predicted No	Percent Correct
Yes	22,758	28,601	44.3%
No	61,828	201,721	76.5%
Overall	26.9%	73.1%	71.3%

Table C4

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed without GPA

	IF	THEN
Node 4	Age 14.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander or unknown ethnicity	11.6% probability
Node 1	Age 14.5 years or younger	12.9% probability
Node 6	Older than 14.5 years of age AND Caucasian, Asian, or unknown ethnicity	18.8% probability
Node 3	Age14.5 years or younger AND African American or American Indian	20.9% probability
Node 2	Older than 14.5 years of age	26.8% probability
Node 5	Older than 14.5 years of age AND Hispanic, African American, Biracial, American Indian, or Pacific Islander	31.2% probability

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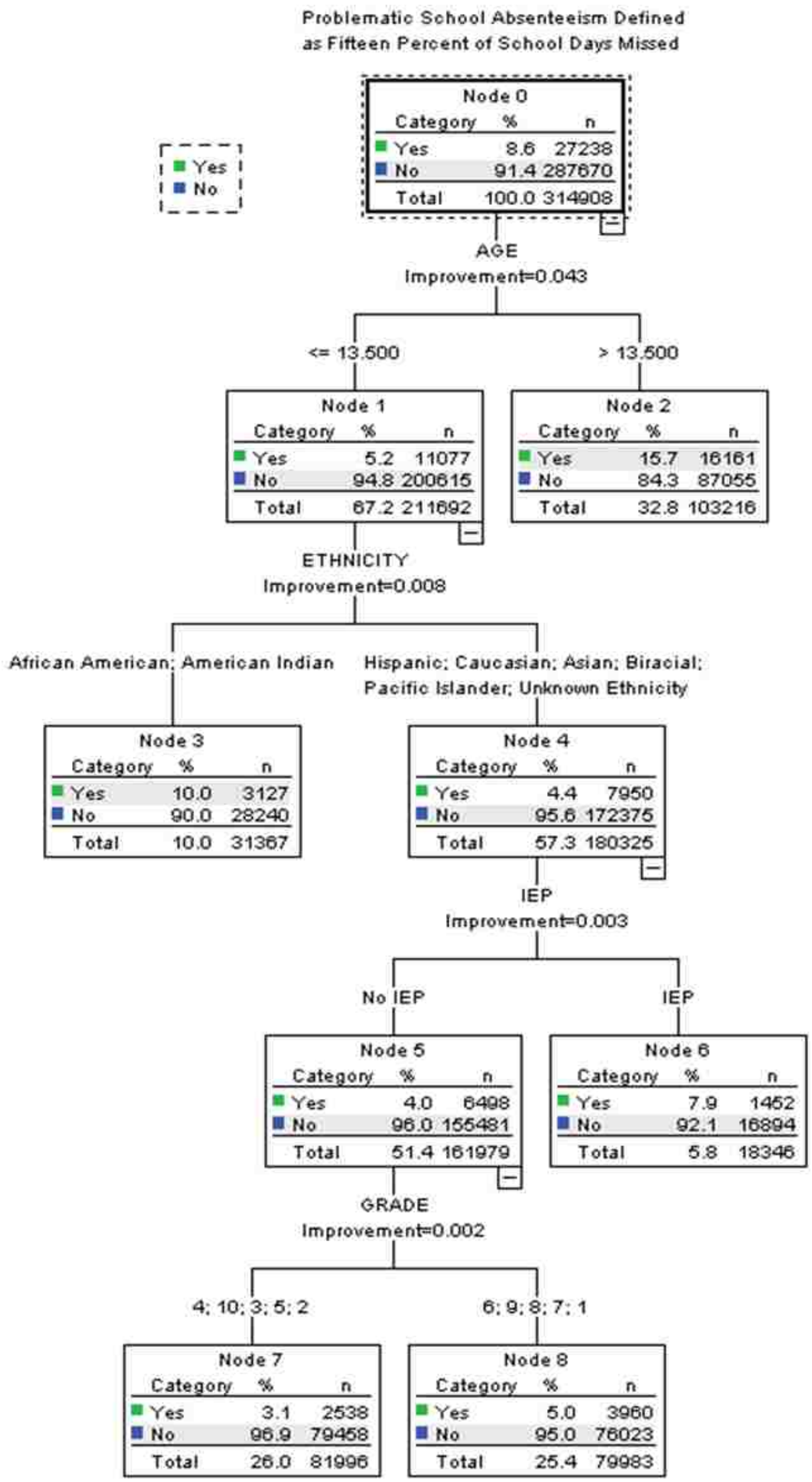

Figure C3. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 15% of full school days missed without GPA

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Table C5

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed without GPA

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	19,288	7,950	70.8%
No	115,295	172,375	59.9%
Overall	42.7%	57.3%	60.9%

Table C6

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed without GPA

	IF	THEN
Node 7	Age 13.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity AND not IEP eligible AND a grade level of 2, 3, 4, 5, or 10	3.1% probability
Node 5	Age 13.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity AND not IEP eligible	4.0% probability
Node 4	Age 13.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity	4.4% probability
Node 8	Age 13.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity AND not IEP eligible AND a grade level of 1, 6, 7, 8, or 9	5.0% probability
Node 1	Age 13.5 years or younger	5.2% probability
Node 6	Age 13.5 years or younger AND Hispanic, Caucasian, Asian, Biracial, Pacific Islander, or unknown ethnicity AND eligible for an IEP	7.9% probability
Node 3	Age 13.5 years or younger AND African American or American Indian	10.0% probability
Node 2	Older than 13.5 years of age	15.7% probability

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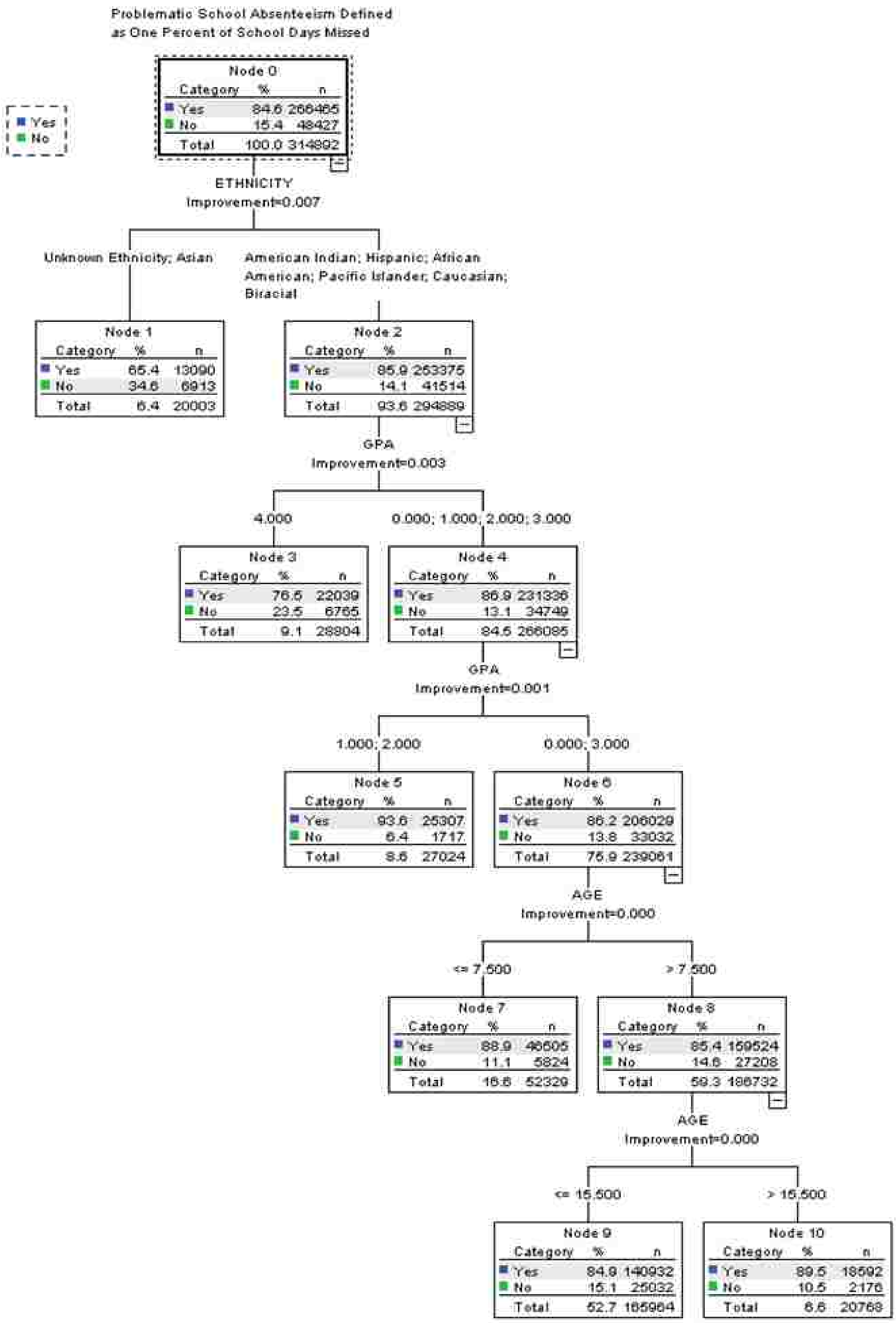

Figure C4. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 1% of full school days missed without grade level

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Table C7

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed without Grade Level

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	253,375	13,090	95.1%
No	41,514	6,913	14.3%
Overall	93.6%	6.4%	82.7%

Table C8

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 1% of Full School Days Missed without Grade Level

	IF	THEN
Node 1	Asian or unknown ethnicity	65.4% probability
Node 3	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander AND a GPA between 3.01 and 4.00	76.5% probability
Node 9	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 15.5 years or younger	84.9% probability
Node 8	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND older than 7.5 years of age	85.4% probability
Node 2	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander	85.9% probability
Node 6	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 2.01 and 3.00	86.2% probability
Node 4	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific	86.9% probability

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	Islander AND an unknown/nonexistent GPA or GPA between 0.00 and 3.00	
Node 7	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 7.5 years or younger	88.9% probability
Node 10	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander AND an unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND older than 15.5 years of age	89.5% probability
Node 5	Hispanic, African American, American Indian, Caucasian, Biracial, or Pacific Islander AND a GPA between 0.00 and 2.00	93.6% probability

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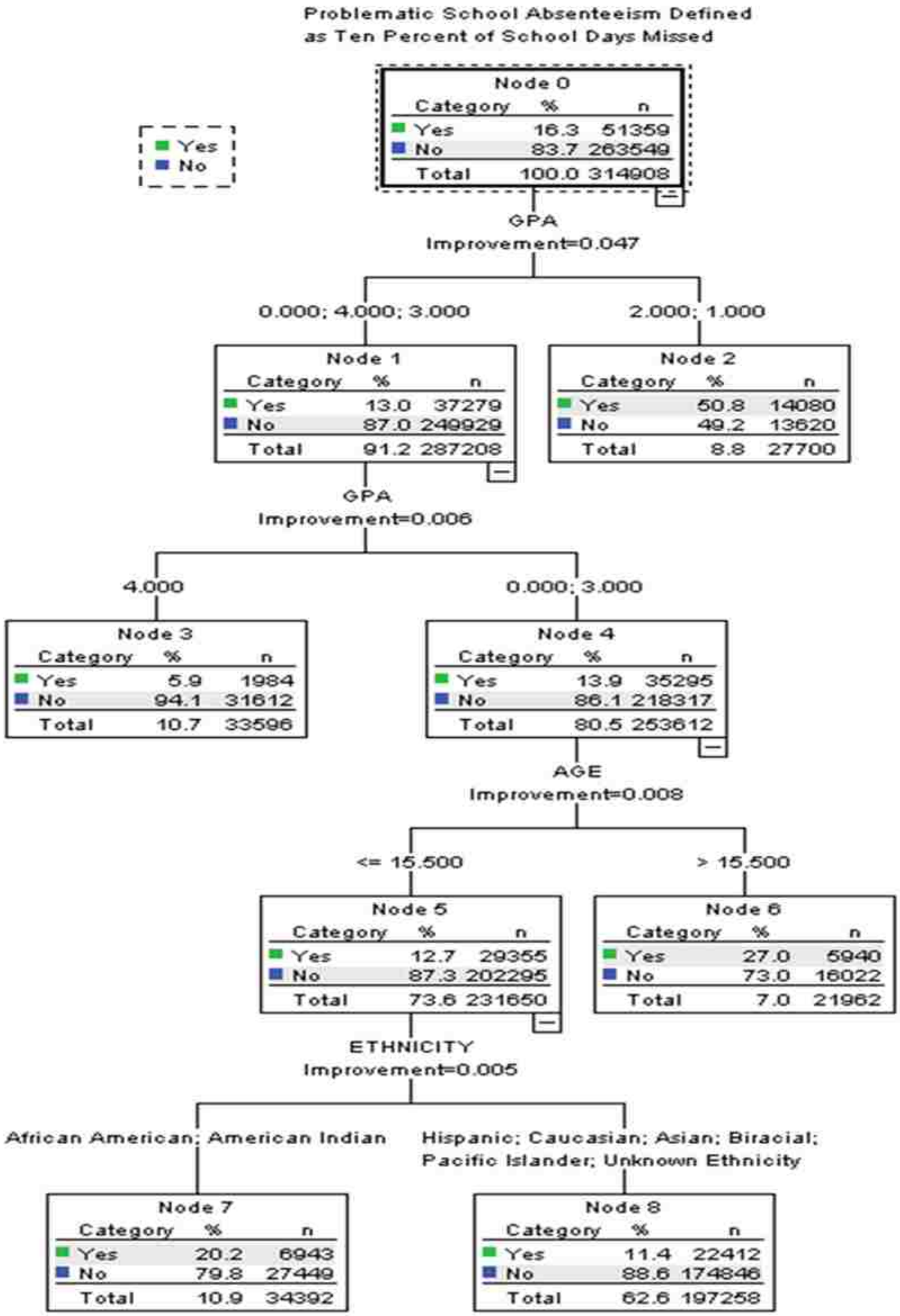

Figure C5. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 10% of full school days missed without grade level

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Table C9

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed without Grade Level

Problematic School Absenteeism	Predicted *Yes*	*No*	Percent Correct
Yes	26,963	24,396	52.5%
No	57,091	206,458	78.3%
Overall	26.7%	73.3%	74.1%

Table C10

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 10% of Full School Days Missed without Grade Level

	IF	THEN
Node 3	A GPA between 3.01 and 4.00	5.9% probability
Node 8	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 15.5 years or younger AND Hispanic, Caucasian, Asian, Pacific Islander, or unknown ethnicity	11.4% probability
Node 5	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 15.5 years or younger	12.7% probability
Node 1	An unknown/nonexistent GPA or GPA between 2.01 and 4.00	13.0% probability
Node 4	An unknown/nonexistent GPA or GPA between 2.01 and 3.00	13.9% probability
Node 7	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 15.5 years or younger AND African American or American Indian	20.2% probability
Node 6	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND older than 15.5 years of age	27.0% probability
Node 2	A GPA between 0.00 and 2.00	50.8% probability

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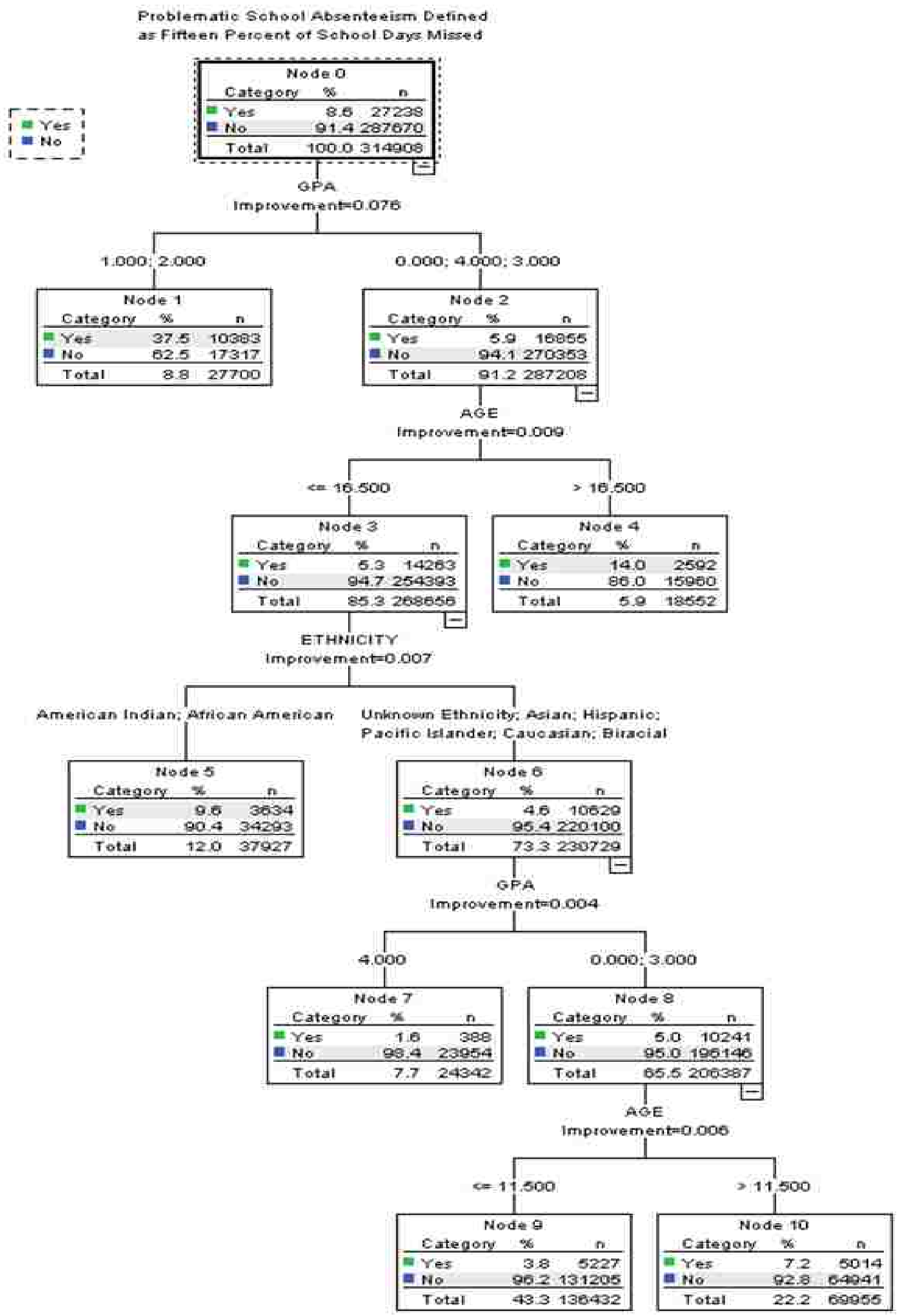

Figure C6. Total sample classification tree of risk factors for problematic school absenteeism defined as ≥ 15% of full school days missed without grade level

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Table C11

Total Sample Classification Table for the Final Model of Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed without Grade Level

Problematic School Absenteeism	Predicted *Yes*	Predicted *No*	Percent Correct
Yes	16,609	10,629	61.0%
No	67,570	220,100	76.5%
Overall	26.7%	73.3%	75.2%

Table C12

Total Sample IF-THEN Rules for the Probability of Exhibiting Problematic School Absenteeism Defined as ≥ 15% of Full School Days Missed without Grade Level

	IF	THEN
Node 7	GPA between 3.01 and 4.00 AND age 16.5 years or younger AND Asian, Hispanic, Caucasian, Biracial, Pacific Islander, or unknown ethnicity	1.6% probability
Node 9	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 11.5 years or younger AND Asian, Hispanic, Caucasian, Biracial, Pacific Islander, or unknown ethnicity	3.8% probability
Node 6	An unknown/nonexistent GPA or GPA between 2.01 and 4.00 AND age 16.5 years or younger AND Asian, Hispanic, Caucasian, Biracial, Pacific Islander, or unknown ethnicity	4.6% probability
Node 8	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND age 16.5 years or younger AND Asian, Hispanic, Caucasian, Biracial, Pacific Islander, or unknown ethnicity	5.0% probability
Node 3	An unknown/nonexistent GPA or GPA between 2.01 and 4.00 AND age 16.5 years or younger	5.3% probability
Node 2	An unknown/nonexistent GPA or GPA between 2.01 and 4.00	5.9% probability

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Node 10	An unknown/nonexistent GPA or GPA between 2.01 and 3.00 AND older than 11.5 years of age AND Asian, Hispanic, Caucasian, Biracial, Pacific Islander, or unknown ethnicity	7.2% probability
Node 5	An unknown/nonexistent GPA or GPA between 2.01 and 4.00 AND age 16.5 years or younger AND African American or American Indian	9.6% probability
Node 4	An unknown/nonexistent GPA or GPA between 2.01 and 4.00 AND older than 16.5 years of age	14.0% probability
Node 1	GPA between 0.00 and 2.00	37.5% probability

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APPENDIX D

Tables for Committee Requested Regression Analyses

Table D1

Logistic Regression for Problematic School Absenteeism defined as 1% of Full School Days Missed

	Wald	***p***	**Odds Ratio**	**95% C.I. for Odds Ratio**	
				Lower	**Upper**
Female	743.524	<.01*	1.663	1.604	1.725
Asian	268.184	<.01*	.486	.445	.529
Hispanic	4.197	.040*	1.084	1.003	1.170
African American	4.891	.027*	.906	.829	.989
Caucasian	51.236	<.01*	1.334	1.233	1.444
Pacific Islander	3.806	<.01*	1.339	1.134	1.580
Age	554.567	<.01*	1.196	1.178	1.214
GPA	3977.376	<.01*	.442	.431	.454

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Table D2

Logistic Regression for Problematic School Absenteeism defined as 10% of Full School Days Missed

	Wald	***p***	**Odds Ratio**	**95% C.I. for Odds Ratio**	
				Lower	**Upper**
Female	1,104.395	<.001*	1.812	1.749	1.876
Asian	42.379	<.001*	.694	.622	.775
African American	4.140	.042*	.917	.844	.997
Age	2,217.227	<.001*	1.415	1.394	1.435
GPA	15,264.564	<.001*	.249	.244	.255
IEP Eligibility	24.126	<.001*	1.147	1.086	1.212

Table D3

Logistic Regression for Problematic School Absenteeism defined as 1% of Full School Days Missed

	Wald	***p***	**Odds Ratio**	**95% C.I. for Odds Ratio**	
				Lower	**Upper**
Female	739.551	<.001*	1.794	1.720	1.871
Asian	24.766	<.001*	.694	.601	.801
Age	2,237.997	<.001*	1.533	1.506	1.560
GPA	13,775.975	<.001*	.208	.203	.214
IEP Eligibility	21.746	<.001*	1.161	1.090	1.236

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CURRICULUM VITAE

KYLEIGH K. SKEDGELL (SHELDON)
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EDUCATION AND TRAINING

University of Nevada, Las Vegas **January 2016 – Present**
Doctoral Student in APA-Accredited Clinical Psychology Program
Dissertation: Defining Problematic School Absenteeism Using Nonparametric Modeling

University of Nevada, Las Vegas **August 2013 – December 2015**
Masters Student in APA-Accredited Clinical Psychology Program
Thesis: Differences in Absenteeism Severity among Community Youth

Hope College **August 2009 – May 2013**
Holland, MI
Undergraduate Student
Major: Psychology

HONORS AND AWARDS

UNLV Patricia Sastaunik Scholarship Award	2017
UNLV Sterling Scholarship Award	2017
UNLV Summer Doctoral Research Fellowship	2017
UNLV Patricia Sastaunik Scholarship Award	2016
UNLV Summer Session Scholarship Award	2016
UNLV Student Summer Faculty Research Award	2016
APAGS ACT Excellence in Campus Leadership Award	2016
UNLV Summer Session Scholarship Award	2015
Hope College Team Scholar All-American Award	2013
Hope College Dean's List	2009 – 2013

PRE-DOCTORAL PRACTICUM TRAINING

The Children's Specialty Center of Nevada **August 2017 – Present**
Primary Supervisor: Danielle T. Bello, Ph.D.
Doctoral Practicum Student

Conducting comprehensive neuropsychological assessments and writing integrated reports for children and adolescents with chronic medical conditions in a pediatric hospital setting. Typical referrals include youths being treated in the hospital's oncology, hematology, rheumatology, and genetic disorders clinics. Primary psychological diagnoses include a wide range of cognitive disabilities, neurodevelopmental disorders, learning disorders, ADHD, and anxiety disorders. Also functioning as part of a multidisciplinary treatment

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team with medical personnel and attending weekly grand rounds as well as bi-monthly Sickle Cell Clinic. Receiving weekly individual supervision.

The Pediatric Specialty Clinic **June 2016 – April 2017**
The PRACTICE: A UNLV Community Mental Health Center
Primary Supervisor: Adrianna Wechsler-Zimring, M.Ed., Ph.D.
Doctoral Practicum Student

Provided evidence-based intervention to children, adolescents, and families at high risk for hospitalization due to complex medical, psychiatric, and behavioral health concerns. Typical referrals included feeding and eating disorders, neurodevelopmental disorders, and atypical self-harming behaviors. Also coordinated care with other providers (e.g., pediatricians, cardiologists, geneticists, registered dieticians, and schools). Utilized cognitive-behavioral and dialectical-behavioral orientations as the main forms of intervention. Received weekly individual supervision as well as monthly multidisciplinary team case consultation.

The Offices of Adrianna Wechsler-Zimring, M.Ed., Ph.D. P.C. **June 2016 – April 2017**
Primary Supervisor: Adrianna Wechsler-Zimring, M.Ed., Ph.D.
Doctoral Practicum Student

Provided evidence-based assessment, consultation, and intervention to culturally and economically diverse children, adolescents, and families in a private practice setting, as most referrals have been or currently were in foster care or the juvenile justice system and on Medicaid. Typical referrals included a wide range of neurodevelopmental disorders, feeding and eating disorders, anxiety disorders, obsessive-compulsive disorders, trauma- and stressor-related disorders, and disruptive, impulse-control, and conduct disorders, among others. Also provided in-home evidence-based intervention for adolescents with significant executive functioning deficits (i.e., attention-deficit hyperactivity disorder and/or autism spectrum disorder). Comprehensive assessment focused on differential diagnosis, providing appropriate referrals, and developing treatment plans. Utilized cognitive-behavioral and dialectical-behavioral orientations as the main forms of intervention. Received weekly individual supervision.

The PRACTICE: A UNLV Community Mental Health Center **January 2016 – September 2016**
Primary Supervisor: Noelle Lefforge, Ph.D.
Doctoral Practicum Student

Provided evidence-based group treatment to children and adolescents with various emotional and behavioral concerns and their parents at the on-campus training community clinic. Typical referrals included generalized anxiety disorder, social anxiety disorder, and panic disorder. Utilized a cognitive-behavioral orientation as the main form of intervention. Received weekly group supervision.

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The UNLV Child School Refusal and Anxiety Disorders Clinic **September 2015 – May 2016**

Primary Supervisor: Christopher Kearney, Ph.D.
Doctoral Practicum Student

Provided evidence-based intervention services to children and adolescents with significant school-based anxiety and other co-morbid anxiety disorders (e.g., selective mutism) in clinic, school, and community settings. Also provided consultation services to school personnel and trained and supervised undergraduate research assistants. Utilized a manualized cognitive-behavioral treatment that emphasized exposure-based techniques as the main form of intervention in individual, family, and group formats. Received weekly individual supervision.

The PRACTICE: A UNLV Community Mental Health Center **August 2015 – December 2015**

Primary Supervisor: Noelle Lefforge, Ph.D.
Doctoral Practicum Student

Provided group therapy to adults with various emotional, behavioral, and interpersonal concerns at the on-campus training community clinic. Typical referrals included generalized anxiety disorder, social anxiety disorder, and depression. Utilized Bion's Group as a Whole (GAW) orientation as the main form of intervention. Received weekly group supervision.

The PRACTICE: A UNLV Community Mental Health Center **January 2015 – May 2015**

Primary Supervisor: Christopher Heavey, Ph.D.
Doctoral Practicum Student

Provided couples therapy to adults with various emotional and interpersonal difficulties at the on-campus training community clinic. Utilized a cognitive-behavioral orientation as the main form of intervention. Received weekly group supervision.

The PRACTICE: A UNLV Community Mental Health Center **August 2014 – August 2015**

Primary Supervisor: Andrew J. Freeman, Ph.D.
Doctoral Practicum Student

Provided evidence-based assessment and manualized intervention to children and adolescents with various emotional and behavioral concerns and their parents at the on-campus training community clinic. Typical referrals included various anxiety disorders, depression, oppositional defiant disorder, adjustment disorder, and learning disorders. Comprehensive assessment focused on differential diagnosis, providing appropriate referrals, and developing treatment plans. Utilized a cognitive-behavioral orientation as the main form of intervention with problem solving and motivational interviewing. Received weekly individual and group supervision.

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RELATED CLINICAL EXPERIENCE

Mary Free Bed Rehabilitation Hospital **January 2012 – June 2012**
Primary Supervisor: Deb W. Brewer, CCLS
Child Life Specialist Intern

Provided a positive hospital experience for child and adolescent patients and their families by acting as a support system and leading developmentally appropriate games/activities. Received weekly supervision.

SUPPLEMENTAL CLINICAL TRAINING

Doing Business as a Psychologist – Larry Waldman, Ph.D. **September 2017**
1-day training sponsored by the Nevada Psychological Association (NPA)

Prolonged Exposure for PTSD – Thomas Mullin, Ph.D. **February 2017**
1-day training sponsored by the Nevada Psychological Association (NPA)

Why People Die by Suicide – Thomas Joiner, Ph.D. **October 2016**
1-day training sponsored by Nevada Psychological Association (NPA)

Trauma-Focused Cognitive-Behavioral Therapy **August 2016**
Online training course sponsored by the Medical University of South Carolina (MUSC)

Dialectical Behavior Therapy Part II – Alan Fruzetti, Ph.D. **April 2015**
3-day training sponsored by Nevada Psychological Association (NPA)

Dialectical Behavior Therapy Part I – Alan Fruzetti, Ph.D. **February 2015**
3-day training sponsored by Nevada Psychological Association (NPA)

RESEARCH EXPERIENCE

The UNLV Child School Refusal and Anxiety Disorders Clinic **January 2016 – Present**
University of Nevada, Las Vegas
Faculty Advisor/Committee Chair: Christopher A. Kearney, Ph.D
Doctoral Dissertation: *Defining Problematic School Absenteeism Using Non-Parametric Modeling*
Role: Principal Investigator

Contemporary classification models of school absenteeism often employ a multitier approach for organizing assessment and treatment strategies. Researchers have yet to agree, however, on how to objectively define problematic school absenteeism and identify demarcation points for each tier. This study aims to inform a multitier approach by determining the most relevant demographic and academic-related risk factors for

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problematic school absenteeism. Data will be acquired from the Clark County School District of Nevada for all elementary, middle, and high school youth (N = 316,004). Binary recursive partitioning techniques will be utilized to construct classification trees at three distinct cutoffs of absenteeism (e.g., 1%, 10%, and 15% of full school days missed). Risk factors identified at each cutoff may suggest a difference in the profile of a youth as absenteeism becomes more severe from Tier 1 to Tier 2. Profiles of at-risk youth may be shared with school administrators to assist in the development of individualized prevention programs.

Neuropsychology Research Laboratory **July 2015 – December 2015**
University of Nevada, Las Vegas
Faculty Advisor: Daniel Allen, Ph.D.
Study Title: *Social Cognition in Attention-Deficit/Hyperactivity Disorder*
Role: Research Assistant

This study aimed to examine social cognitive functioning abilities in children with attention-deficit hyperactivity disorder. Administered a standard assessment battery consisting of the WISC-V as well as select subtests from the WJ-IV-ACH and the NEPSY-II.

The UNLV Child School Refusal and Anxiety Disorders Clinic **August 2013 – December 2015**
University of Nevada, Las Vegas
Faculty Advisor/Committee Chair: Christopher A. Kearney, Ph.D.
Master's Thesis: *Differences in Absenteeism Severity among Community Youth*
Role: Principal Investigator

School absenteeism is a strong predictor of school dropout. Researchers, however, have yet to agree on the level of absenteeism that warrants the most clinical concern. This study aimed to examine the relationship between school absenteeism severity and family and clinical variables among community youth recruited from two truancy settings in the Clark County School District of Nevada (N = 118). The first set of hypotheses involved family and clinical variables that may predict absenteeism severity evaluated on a dimensional basis via stepwise linear regression. Results revealed obsessions and compulsions as significant predictors of absenteeism severity. The second set of hypotheses involved evaluating potential differences in family and clinical variables between categorically defined levels of absenteeism via multivariate analysis of variance (MANOVA). Results revealed significant differences among internalizing symptoms between specific categorically defined levels of absenteeism, suggesting that 15% of school days missed may be an appropriate clinical cutoff for problematic school absenteeism.

Hope College **August 2012 – December 2012**
Faculty Advisor: Sonja Trent-Brown, Ph.D.
Study Title: *Activity Preference and Self-Efficacy in Kindergarten and First Grade Students*
Role: Research Assistant

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This study aimed to examine the effectiveness of an early intervention nature program administered by the Outdoor Discovery Center to elementary school youths in Holland, MI. Attended school-based nature lessons as well as coded and entered pre- and post-program data into SPSS.

Michigan State University **January 2012 – April 2012**
Graduate Student Advisor: Tami Mannes, M.A.
Study Title: ***The Effect of Tier One Literacy Practice in Preschool Settings***
Role: Research Assistant

This study aimed to examine the role of peer support and child age on the relationship between parental control and child anxiety. Administered pre- and post- literacy assessment measures (i.e., DIBBELS) to pre-school aged children in the Ottawa County School District of Michigan, as well as scored, coded, and entered data into SPSS.

PUBLICATIONS

Skedgell, K. K., Fornander, M., & Kearney, C. A. (2017). Personalized individual and group therapy for multifaceted selective mutism. *Clinical Case Studies, 16*(2), 166-181.
doi:10.1177/1534650116685619

Kearney, C.A., & **Sheldon, K.** (2017). School refusal. In A.E. Wenzel (Ed.), *The SAGE encyclopedia of abnormal and clinical psychology* (pp. 2989-2991). Thousand Oaks, CA: Sage.

Kearney, C. A., & **Sheldon, K. K.** (2017). Evidence-based interventions for school refusal behavior in children and adolescents. In L.A. Theodore (Ed.), *Handbook of evidence-based interventions for children and adolescents* (pp. 279-288). New York: Springer.

Skedgell, K. K., & Kearney, C. A. (2016). Predictors of absenteeism severity in truant youth: A dimensional and categorical analysis. *American Secondary Education, 45*(1), 46-58.

PROFESSIONAL PRESENTATIONS

Fornander, M., **Skedgell, K.**, & Kearney, C. A. (2016). *School Refusal.* Oral presentation at the Nevada Association of School Psychologists Fall Conference: Las Vegas, NV.

Sheldon, K., Fornander, M., & Kearney, C. A. (2016). *Selective Mutism Group Treatment.* Poster presentation at the Selective Mutism Group (SMG) & University of California, Los Angeles (UCLA) Annual Conference: Manhattan Beach, CA.

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Sheldon, K., Fornander, M., & Kearney, C. A. (2016). *ADHD Symptoms in Youth who are Truant.* Poster presentation at the 42nd Annual Conference of the Society for Police and Criminal Psychology: Austin, TX.

Sheldon, K., & Kearney, C. A. (2015). *Differences in Absenteeism Severity among Community Youth*. Oral presentation at the Western Psychological Association 95th Annual Convention: Las Vegas, NV.

Diliberto, R., **Sheldon, K.**, & Kearney, C. A. (2015). *Peer Relationships in Youth with School Refusal or Selective Mutism.* Poster presentation at the Western Psychological Association 95th Annual Convention: Las Vegas, NV.

Sheldon, K., & Kearney, C. A. (2014). *Internalizing and Externalizing Symptoms as Predictors of Truancy Severity in Community Youth*. Poster presentation at the 40th Annual Conference of the Society for Police and Criminal Psychology: Las Vegas, NV.

Sheldon, K. (2014). *School Refusal Behavior: Perceptions of School Climate and Absenteeism Severity*. Oral presentation at the Global Conference on Contemporary Issues in Education: Las Vegas, NV.

Ross, E., Kearney, C. A., & **Sheldon, K.** (2014). *Depression and Dissociation as Predictors of Posttraumatic Symptoms among Community Youth.* Poster presentation at the Association for Psychological Science 26th Annual Convention: San Francisco, CA.

Bednarz, A., Bieri, M, Burke, K., Cameron, L., Hogan, C., Kelso, M., Kostizen, M., McGuire, P., **Sheldon, K.**, Timmer, S., Walker, A., Wilkie, C., & Trent-Brown, S. (2012). *Activity Preference and Self-Efficacy in Kindergarten and First Grade Students.* Poster presentation at the Celebration of Undergraduate Research: Hope College, Holland, MI.

TEACHING EXPERIENCE

Graduate Student Instructor **August 2015 – Present**
General Psychology PSY 101
University of Nevada, Las Vegas

Teaching an undergraduate introductory psychology course. Goals include: 1) develop an understanding of the discipline of psychology, 2) develop scientific values and skills, and 3) foster personal growth. Duties include: assembling and presenting weekly lectures, grading assignments and examinations, and providing a minimum of two office hours. Evaluation scores for eight sections average 4.6 out of 5.

SUPPLEMENTAL TEACHING EXPERIENCE

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Workshop Leader **January 2016**
Behavioral Management of Attention-Deficit Hyperactivity Disorder
New Horizons Center for Learning – Las Vegas, NV

Teaching Assistant **August 2014 – December 2014**
PSY 715: Psychological Assessment of Children
University of Nevada, Las Vegas

Teaching Assistant **October 2012 – December 2012**
Project Charlie: Drug & Alcohol Prevention Program
Holland West Elementary School – Holland, MI

SUPERVISION EXPERIENCE

Peer Clinical Supervisor **June 2016 – August 2016**
PSY 762: Introduction to Supervision

Received training through coursework and provided clinical supervision to psychology doctoral students. Supervision was conceptualized based on Bernard's Discriminant Model and implemented from a cognitive-behavioral orientation. Received group supervision of supervision (including video review) by a licensed clinical psychologist.

LEADERSHIP AND SERVICE

Campus Ambassador **September 2017 – Present**
American Psychological Association (APA)

Responsibilities include hosting interactive advocacy-related presentations, participating in on-going discussions related to timely psychology topics via listserv, and sharing information with program faculty and graduate students.

Undergraduate Mentor **September 2016 – Present**
Outreach Undergraduate Mentorship Program (OUMP)

Responsibilities include meeting with mentees as necessary (e.g., twice a month) to assist in identifying goals, directing to appropriate resources such as scholarships, and providing additional assistance on goal-related tasks such as constructing a curriculum vitae and proofreading personal statements.

Campus Representative **August 2015 – Present**
APAGS Advocacy Coordinating Team (ACT)

Responsibilities include being a voting member on the Executive Board of the Nevada Psychological Association (NPA) and attending monthly conference calls, organizing

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advocacy events, participating in on-going discussions related to timely psychology topics via listserv, and submitting monthly reports.

Committee Chair & Cohort Representative **August 2015 – Present**
Clinical Student Committee (CSC)

Responsibilities include attending monthly department faculty meetings and serving as primary liaison between faculty and graduate students for all program-related updates and events.

PROFESSIONAL BOARDS AND COMMITTEES

UNLV Psychology Department Diversity and Inclusion Committee	2016 – Present
UNLV Psychology Department Clinical Student Committee (CSC)	2015 – Present
Nevada Psychological Association (NPA) Technology/Social Media	2015 – Present
Nevada Psychological Association (NPA) Executive Board	2015 – Present
APAGS Advocacy Coordinating Team (ACT)	2015 – Present

PROFESSIONAL MEMBERSHIPS

APA Division 2: Society for the Teaching of Psychology (STP)	2015 – Present
Graduate Student Teaching Association (GSTA)	2015 – Present
American Psychological Association for Graduate Students (APAGS)	2014 – Present
American Psychological Association (APA)	2014 – Present
Nevada Psychological Association (NPA)	2013 – Present
Western Psychological Association (WPA)	2014 – 2016
Society for Police and Criminal Psychology (SPCP)	2014 – 2016
Association for Psychological Science (APS)	2013 – 2015

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