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Defining Problematic School Absenteeism: Identifying Youth at Risk

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DEFINING PROBLEMATIC SCHOOL ABSENTEEISM: IDENTIFYING YOUTH AT RISK

By

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ABSTRACT

Defining Problematic School Absenteeism: Identifying Youth at Risk

by

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Study 1: School attendance is an important foundational competency for children and adolescents, and school absenteeism has been linked to myriad short- and long-term negative consequences, even into adulthood. Many efforts have been made to conceptualize and address this population across various categories and dimensions of functioning and across multiple disciplines, resulting in both a rich literature base and a splintered view regarding this population. This article (Part 1 of 2) reviews and critiques key categorical and dimensional approaches to conceptualizing school attendance and school absenteeism, with an eye toward reconciling these approaches (Part 2 of 2) to develop a roadmap for preventative and intervention strategies, early warning systems and nimble response, global policy review, dissemination and implementation, and adaptations to future changes in education and technology. This article sets the stage for a discussion of a multidimensional, multi-tiered system of supports pyramid model as a heuristic framework for conceptualizing the manifold aspects of school attendance and school absenteeism.

Study 2: School attendance problems, including school absenteeism, are common to many students worldwide, and frameworks to better understand these heterogeneous students include multiple classes or tiers of intertwined risk factors as well as interventions. Recent studies have

thus examined risk factors at varying levels of absenteeism severity to demarcate distinctions among these tiers. Prior studies in this regard have focused more on demographic and academic variables and less on family environment risk factors that are endemic to this population. The present study utilized ensemble and classification and regression tree analysis to identify potential family environment risk factors among youth (i.e., children and adolescents) at different levels of school absenteeism severity (i.e., 1 + %, 3 + %, 5 + %, 10 + %). Higher levels of absenteeism were also examined on an exploratory basis. Participants included 341 youth aged 5–17 years (M = 12.2; SD = 3.3) and their families from an outpatient therapy clinic (68.3%) and community (31.7%) setting, the latter from a family court and truancy diversion program cohort. Family environment risk factors tended to be more circumscribed and informative at higher levels of absenteeism, with greater diversity at lower levels. Higher levels of absenteeism appear more closely related to lower achievement orientation, active-recreational orientation, cohesion, and expressiveness, though several nuanced results were found as well. Absenteeism severity levels of 10–15% may be associated more with qualitative changes in family functioning. These data may support a Tier 2-Tier 3 distinction in this regard and may indicate the need for specific family-based intervention goals at higher levels of absenteeism severity.

Study 3: School attendance problems are highly prevalent worldwide, leading researchers to investigate many different risk factors for this population. Of considerable controversy is how internalizing behavior problems might help to distinguish different types of youth with school attendance problems. In addition, efforts are ongoing to identify the point at which children and adolescents move from appropriate school attendance to problematic school absenteeism. The

present study utilized ensemble and classification and regression tree analysis to identify potential internalizing behavior risk factors among youth at different levels of school absenteeism severity (i.e., 1+%, 3+%, 5+%, 10+%). Higher levels of absenteeism were also examined on an exploratory basis. Participants included 160 youth aged 6–19 years (*M* = 13.7; SD = 2.9) and their families from an outpatient therapy clinic (39.4%) and community (60.6%) setting, the latter from a family court and truancy diversion program cohort. One particular item relating to lack of enjoyment was most predictive of absenteeism severity at different levels, though not among the highest levels. Other internalizing items were also predictive of various levels of absenteeism severity, but only in a negatively endorsed fashion. Internalizing symptoms of worry and fatigue tended to be endorsed higher across less severe and more severe absenteeism severity levels. A general expectation that predictors would tend to be more homogeneous at higher than lower levels of absenteeism severity was not generally supported. The results help confirm the difficulty of conceptualizing this population based on forms of behavior but may support the need for early warning sign screening for youth at risk for school attendance problems.

ACKNOWLEDGEMENTS

This project is dedicated to my daughter Aria, who made her miraculous entrance into the world right in the middle of my dissertation. I have never been more appreciative of the joy her constant laughter and smiles bring to my life. Just as my mother did before me, I hope I will teach her the importance of hard work and perseverance. Thank you to my husband, Seth, for supporting and encouraging my dreams. A special thank you to my lab mates, Kyleigh Skedgell and Victoria Bacon, for their partnership as we work towards our degrees. Finally, I extend thanks to my committee members, Drs. Coughenour, Donohue, and Paul, for their time and to my committee chair, Dr. Christopher Kearney, for his guidance throughout this project.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

School absenteeism

School absenteeism is an educational crisis; eight million American students in the 2013-2014 school year missed more than three weeks of school (National Center for Education Statistics, 2016). National rates of school absenteeism have been increasing in recent years, up from 6.8 million students in the 2014-2015 school year (Bauer, Liu, Schanzenbach, & Shambaugh, 2018). Of the students who display school absenteeism, about 50% do so for multiple school years and 25% miss at least two months of school (Balfanz & Byrnes, 2012; Kearney, 2016). School absenteeism is also a problem in Nevada. Over the last 15 years, 1,323 to 5,210 of Nevada students were identified as chronically absent per year (Nevada Department of Education, 2018).

The highest rates of school absenteeism occur in high school (20%; Department of Education, 2016) and high poverty urban and rural schools (33% & 25% respectively; Balfanz & Byrnes, 2012). In comparison, partial absences are defined as tardiness and skipping or missing certain classes. As many as 54.6% of high school students endorsed “sometimes” skipping a class, and 13.1% endorsed “often” skipping a class (Guare & Cooper, 2003). The prevalence rates of morning tardiness range from 4.5-9.5% (Kearney, 2001). Nationally, tardiness and skipping classes result in 45% of all disciplinary referrals at school (24%, and 21% respectively; Spaulding et al., 2010).

The increase in school absenteeism across the country has led to multiple federal and state initiatives to address this problem. President Obama launched the My Brother’s Keeper initiative (Office of the Press Secretary, 2014) and the U.S. Department of Education published a joint effort among multiple agencies stating the nature of attendance problems (U.S. Department of Education, 2015b). President Obama also released the Community Toolkit to Address and Eliminate Chronic Absenteeism (U.S. Department of Education, 2016) and held a national summit (U.S. Department of Education, 2016). These initiatives led to revisions to the Every Student Succeeds Act (ESSA) in 2015 (U.S. Department of Education, 2015a) and to an update in 2017 (U.S. Department of Education, 2017). At the state level, Nevada legislatures enacted a definition of truancy (NRS 392.130, 2007; NRS 392.210, 2013) and administrative sanctions for absenteeism (NRS 392.144, 2013). Similarly, Clark County School District (CCSD) began the Reclaim Your Future Initiative (Clark County School District, 2011) and employed the Truancy Diversion Program in 2002 (Clark County School District, 2018) and the Student Attendance Review Board (SARB; Clark County School District, n.d.) in 2013.

School absenteeism is a multidisciplinary problem that refers to any absence from school by school aged-youth (Kearney, 2008). School absences can either be problematic or nonproblematic. The majority of absences are nonproblematic as they are brief, do not impact functioning, and are self-corrected (Kearney, 2008). Examples of nonproblematic absenteeism include situations that are verified by parents or school officials such as emergencies, illnesses, holidays, or any other unexpected circumstances (Kearney & Albano, 2007). On the other hand, problematic school absenteeism impairs youth or family functioning. Currently, there are no consistent defining cutoffs for problematic school absenteeism in research or school districts (Jimerson, Burns, & VanDerHeyden, 2016; Lyon & Cotler, 2007; Spruyt, Keppens, Kemper, & Bradt, 2016). Currently utilized definitions in the literature lack utility for school personnel and are not used by school districts (Attendance Works, 2016; National Center for School

Engagement, 2005; Schanzenbach, Bauer, & Mumford, 2016; Spruyt et al., 2016; U.S. Department of Education Office of Safe and Drug-Free Schools, 2007).

The current, multifaceted study aimed to address this gap in the literature by supporting a precise definition of problematic school absenteeism. The study also aimed to identify specific subgroups of youth at various levels of risk for displaying problematic school absenteeism based upon family environment and youth psychopathology. Findings of the current study provide school officials with specific guidelines for assessing problematic school absenteeism, categorizing students into tiers based on their level of severity, and employing specific interventions. Identifying a specific definition of problematic school absenteeism that resonates with and is utilized by school districts and researchers alike is vital. Doing so, will also lead to an accurate identification of the severity of the problem and encourage the identification and utilization of feasible solutions (David, Cristea, & Hofmann, 2018; Maynard et al., 2015). Definitions of problematic school absenteeism used in the literature and by school districts are reviewed below.

Terminology

Various terms have been used to describe attendance difficulties in school-age youth (Kearney, 2016; Table 1). Early researchers conceptualized attendance difficulties as delinquent behavior and youth who lacked morals, respect, and ambition (Kline & Hall, 1898). Conduct-based conceptualizations, such as delinquency or truancy, dominated the field until the introduction of an anxiety-based conceptualization in the early 1930s. Broadwin (1932) proposed that conduct-based explanations do not adequately describe attendance difficulties and instead should address the role of anxieties or fears. This shift in the field is reflected in the move from a primarily conduct-based conceptualization to the inclusion of anxiety-based conceptualizations (Kearney, 2008).

Table 1

Key Definitions Related to Problematic School Absenteeism

Term	Definition
Delinquency	Akin to conduct disorder refers to rule-breaking behaviors and status offenses such as stealing, physical and verbal aggression, property destruction, underage alcohol or tobacco use, and violations of curfew and expectations for school attendance (Frick & Dickens 2006; McCluskey, Bynum, & Patchin, 2004)
Truancy	Illegal, unexcused absence from school; the term may also be applied to youth absenteeism marked by surreptitiousness, lack of parental knowledge or youth anxiety, criminal behavior and academic problems, intense family conflict or disorganization, or social conditions such as poverty (Fantuzzo, Grim, & Hazan, 2005; Fremont, 2003; Reid, 2003)

School phobia	Fear-based absenteeism, as when a youth refuses school due to fear of some specific stimulus such as a classroom animal or fire alarm (Tyrell, 2005)
Separation	Excessive worry about detachment from primary caregivers and *anxiety* reluctance to attend school (Hanna, Fischer, & Fluent, 2006)
School refusal	A broader term referring to anxiety-based absenteeism, including panic and social anxiety, and general emotional distress or worry while in school (Suveg, Aschenbrand, & Kendall, 2005)
School refusal behavior	An even broader term referring to any youth-motivated refusal to attend school or difficulty remaining in classes for an entire day, whether anxiety-related or not (Kearney & Silverman, 1996)

Note. Adapted from "An Interdisciplinary Model of School Absenteeism in Youth to Inform Professional Practice and Public Policy," by C.A. Kearney, 2008, *Educational Psychology Review, 20,* p. 259. Copyright 2008 by Springer Science + Business Media, LLC. Adapted with permission.

The term school refusal behavior was first proposed by Kearney and Silverman (1996) as a continuum encompassing youth aged 5-17 years with self-motivated difficulty staying in school or refusal to attend school (Figure 1). School refusal behavior thus includes many historical definitions or conceptualizations of youth school attendance difficulties. Youth on the continuum all share the desire to miss school.

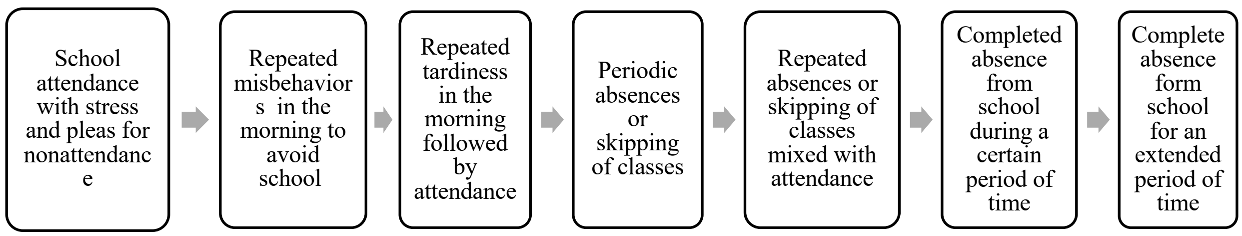

Figure 1. Continuum of school refusal behavior based on attendance. Adapted from *School Refusal Behavior in Youth: A Functional Approach to Assessment and Treatment* (p. 7), by C. A. Kearney, 2000, Washington, D.C.: American Psychological Association. Copyright 2000 by the American Psychological Association. Adapted with permission.

Definitions of problematic school absenteeism in the literature range from 1% to 40% of full school days missed (Berg et al., 1993; Egger, Costello, & Angold, 2003) and may include functional criteria such as impact to the student's individual, family, or academic functioning (Kearney, 2008). Various terms also describe problematic school absenteeism in the literature including persistent school non-attendance, school attendance problems, school nonattendance, persistent absenteeism, school absenteeism, school refusal, and school refusal behavior. The following definitions have been utilized in the literature.

Table 2

Definitions of Problematic School Absenteeism in the Literature.

Author	Year	Definition	Functional Criteria
Berg et al.	1993	≥40% of school days in a semester (36 full school days)	n/a
Thornton, Darmody & McCoy	2013	≥11% of school days (20 full school days)	n/a
Melvin et al.	2017	≥50% of school days in the past 4-weeks (10 full school days)	n/a
McKay-Brown et al.	2018	≥50% of school days (15 full school days) or frequently leaving school early in the past 6-weeks	Or severe difficulty attending classes for at least 6-weeks
Kearney	2008	≥25% of school during the last two weeks (2.5 school days)	Or severe difficulty attending classes that impaired one's individual or family functioning
Knollmann, Reissner, & Hebebrand	2018	≥25% of school during the last two weeks (2.5 school days) or ≥13% of school during the last 15 weeks (10 school days)	n/a

Honjo et al.	2001	≥17% of school days per year (30 full school days)	n/a
Department of Education	2016	≥10% of school days (15 full school days)	n/a
Walter et al.	2010	≥8% of school days (14 full school days) or ≥50 classes skipped on the most recent report card	n/a
Last & Strauss	1990	1 missed day in 2-weeks (mild), 1 day missed per week (moderate), missed several days per week (severe), missed weeks of school (extreme)	n/a
King & Bernstein	2001	n/a	Difficulty attending school with emotional distress (i.e., anxiety and depression)
Egger et al.	2003	≥1% of school days (at least ½ day)	n/a
Flannery, Frank & McGrath Kato	2012	≥1% of school days (at least one day without permission)	n/a
Pflug & Schneider	2016	Any school days missed during the previous seven school days	n/a
Reissner et al.	2018	Unexcused attendance for at least several hours	n/a

Current definitions of problematic school absenteeism in the literature are not useful to school districts and, therefore, are not used (Spruyt et al., 2016). The theoretical nature of many definitions coupled with the lack of consensus among researchers leads school districts to identify their own, individualized, definitions. Definitions of problematic school absenteeism used by school districts range from 3% to 10% (Chu, Guarino, Mele, O'Connell, & Coto, 2018; Department for Education, 2016) and often do not include the functional criteria used in the literature. School personnel also use various terms to describe problematic school absenteeism including chronic absenteeism, school refusal behavior, school attendance problems, habitual truant, and truant. The range of definitions and terms used to describe problematic school absenteeism creates barriers to comparing data across districts, applying data-based decision-making models, and employing appropriate interventions. School districts and states have used the following definitions.

Table 3

Definitions of Problematic School Absenteeism in State Law

State	Definition	Law
Alabama	HT= 5 school days in a year	Alabama Code 16-28-1, et seq.
Alaska	10% or more of full school days	AS 14.30.010
Arizona	10% of full school days	Ariz. Rec. Stat. § 15-803

Arkansas	10% of full school days	Ark. Code. § 6-18-222
California	T= 3 full school days or tardy/absent more than 30 minutes in 3 full school days; HT= identified as truant 3 or more times in a year	Cal. Educ. Code § 48260 & 48262
Colorado	4 full school days in a month or 10full school days in a year	Colo. Rev. Stat. § 22-33-107
Connecticut	20 unexcused absences in a year	Conn. Gen. Stat. § 10-200
Delaware	3 full school days in a school year	Del. St. Ti. 14, § 2721
Florida	15 unexcused absences in 90 days	Fla. Rev. Stat. § 1003.01
Georgia	5 or more full school days in a year	O.C.G.A. § 20-2-735
Hawaii	15 or more full school days in a year	Hawaii Rev. Stat. §302A-1132
Idaho	10 or more full school days in a grading period	School District 272: Policy 522
Illinois	10% or more of the previous 180 school days	Ill. Rev. Stat. Cj. 105, PARA. 5/262A
Indiana	T= 3 full school days or 3 or more tardies; HT= identified as truant 2 or more times in a year	Ky. Rev. Stat. Ann. § 159.150
Iowa	8 or more unexcused absences	Iowa Code Chapter 299
Kansas	3 consecutive full school days, 5 full school days in a semester, or 7 full school days in a school year	KS Stat § 72-3120 (2017)

Kentucky	6 full or partial days of school	Ken. Educ. Code 159.010, et seq.
Louisiana	5 full school days or 5 tardies in a month	La. Rev. Stat. Ann. § 17:233
Maine	10 full school days	Me. Rev. Stat. Ann TIT. 20-A, 3272
Maryland	8 full school days in a quarter, 15 full school days in a semester, or 20 full school days in a year	Md. Code, Education § 7–302.2
Massachusetts	5 or more unexcused absences in a school year, 5 or more tardies, or 2 or more missed classes/periods	Mass. Gen. Law Chapter 76, section 1
Michigan	10 unexcused absences in a year	Mich. S.B. 103
Minnesota	7 full school days in a year	Minn. Rev. Stat. § 260C.007
Mississippi	10% or more of full school days	MS Code § 37-13-91
Missouri	8 school days or partial school days during a year	Mo. Rev. Stat. 167.031
Montana	9 or more full school days or 54 or more parts of a day in a year	Montana Code 41-5-103
Nebraska	20 full school days per year or the hourly equivalent	Neb. 644, 843 N.W.2d 665 (2014)
Nevada	T= 1 or more unexcused absences; HT= identified as truant 3 or more times in a year	Nev. Rev. Stat. Ann. § 392. 130 & 392.140

New Hampshire	10 half school days	NH General Court RSA 189
New Jersey	10% or more of full school days	N.J.A.C. 6A:32-8.3
New Mexico	T= 5 absences in a 20-day period; HT= 10 or more unexcused absences in a year	N.M. Stat. Ann § 22-12-9
New York	10 consecutive full school days or 20 full school days in a 4-month period	NYCRR §104.1(i)(2)(iii)
North Carolina	10 or more unexcused absences	G.S. 115C-381
North Dakota	3 consecutive school days during either the first half or the second half of a year, 6 half days during either the first half or the second half of a school or school district's calendar, or 21 class periods	NDCC 15.1-20-02.1
Ohio	HT= when a student misses more than 5 consecutive school days, 7 or more school days in a month, 12 or more school days in a year. CT= 7 or more consecutive full school days, 10 or more full school days in a month, or 15 or more full school days in a year	Ohio Rev. Code 2151.011
Oklahoma	10% of full school days	Ord. No. 24028, § 1, 3-2-10
Oregon	8 unexcused one-half days or 4 full school days in any 4-week period	Oregon Revised Statute 339.065

Pennsylvania	3 or more full school days	Pa. Stat. Ann. TIT. 24, § 13-1333
Rhode Island	10 unexcused absences, tardies, or early dismissals	Rhode Island S.L. 16-19-1
South Carolina	3 consecutive unlawful absences or 5 unlawful absences in a year	SC Code of Reg. Ch. 43-274
South Dakota	T= any unauthorized absence for a full or part of a school day	Code Section 13-27-1, et seq.
Tennessee	5 unexcused absences in a year	Tennessee Code Annotated 49-6-3007
Texas	10 or more days within a 6-month period or 3 or more days in a 4-week period	Tex. Educ. Code Ann. § 25.094
Utah	T= any unexcused absence; HT= more than 2 truancy citations in a school year or 8 absences in a year	Utah Code Ann. § 53A-11-101
Vermont	10 or more full school days in a year	16 V.S.A. §1121, Act 44, Section 46
Virginia	10 or more unexcused absences in a year	Code of Virginia § 46.2-323
Washington	7 unexcused absences per month or 10 in a year	RCW 28A.225.035
West Virginia	10 or more unexcused absences in a year	West Virginia Code 18.8.1
Wisconsin	5 or more full school days	Wis. Rev. Stat. § 118.16
Wyoming	5 or more unexcused full school days	Wyo. Stat. Ann. § 21-4-101

Note. HT= Habitual truant; T= truant; CT= Chronic truancy.

Despite the extensive absenteeism literature base, a lack of an agreed-upon definition of problematic school absenteeism exists (Jimerson et al., 2016; Lyon & Cotler, 2007) leading to complicated, and often counteracting, early identification systems and an inability to access effective treatments or interventions (David et al., 2018; Maynard et al., 2015). Current definitions in the literature lack utility for school personnel and are not used by school districts (Attendance Works, 2016; National Center for School Engagement, 2005; Schanzenbach et al., 2016; Spruyt et al., 2016; U.S. Department of Education Office of Safe and Drug-Free Schools, 2007). Further, procedures used to report absences have been found to vary among teachers, schools, districts, and states (U.S. Department of Education Office of Safe and Drug-Free Schools, 2007). Specific and measurable definitions of problems and levels of severity are crucial to the utility of data-based decision making commonly used in modern education. The identification of a specific definition of problematic school absenteeism that resonates with and is utilized by school districts is vital.

The current, multifaceted study aimed to address this gap in the literature by supporting a precise definition of problematic school absenteeism. The study also aimed to identify specific subgroups of youth at various levels of risk for displaying problematic school absenteeism based upon family environment and youth psychopathology. Multi-tiered systems of support (MTSS) models provide a theoretical framework to identify more pristine distinctions of problematic school absenteeism among the tiers. Doing so, provides school-based personnel with specific guidelines for assessing problematic school absenteeism, categorizing students into tiers based on their level of severity, and employing interventions specific to each tier. The following section defines MTSS and distinguishes this model from similar models.

Multi-tiered systems of support

MTSS is a form of data-based program modification (DBPM) used to make formula-based decisions about student needs to increase their academic and general functioning (Jimerson et al., 2016). DBPM includes data collection, evaluation, collaboration, consultation, interventions, and progress monitoring (Deno, 2016). DBPM has five assumptions, (1) hypotheses are the outcome of an intervention for a student, (2) intervention hypotheses are well tested by single-case designs with repeated data, (3) modifications of general education programs for a student require empirical testing, (4) crucial signs of education functioning require identification and data support, and (5) well-trained professionals are capable of drawing conclusions from data (Deno, 2016). DPBM's ability to assess, screen, and assign interventions is dependent on empirically measured and clearly defined variables (Jimerson et al., 2016). Table 4 describes the practical implications of DPBM.

Table 4

Implications of Data-Based Decision-Making for Practice.

1. Establish common goals and the data that will be used by all to determine whether the goals are being met

2. Choose long-range goals on which progress can be measured for at least an entire school year so that interventions can be evaluated using the data

3. Treat interventions as hypotheses whose effects will be revealed in the data and be prepared to try alternatives when interventions are not leading to goal attainment

4. Continually work at improving the reliability and validity of the data and the criteria you are using to decide whether students should continue in their current intervention levels or should be moved to different levels

5. Create regular in-service training procedures to assure that all those collecting and using data to make decisions understand how to collect the data, why the data are being collected, how to interpret the data, and how to make the decisions

6. Increase the frequency with which student progress is measured and the responsiveness of the intervention system as the students move to more intense levels of intervention

7. Recognize that even evidence-based interventions do not work for every student and design your program in such a way as to enable teachers to find or create and test alternative interventions when evidence-based interventions have not been effective

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Note. Reprinted from "Data-Based Decision Making." In S. R. Jimerson, M. K. Burns, & A. M. VanDerHeyden (Eds.), *Handbook of Response to Intervention: The Science and Practice of Multi-Tiered Systems of Support* (2nd ed.), p. 26. Copyright 2016 by Springer.

Multiple forms of DBPM exist. The most common forms include response to intervention (RTI), positive behavior intervention supports (PBIS) or program-wide positive behavior support (PWPBS), and, more recently, multi-tiered systems of support (MTSS). Figure 2 depicts the similarities and differences between these models, with MTSS represented by the intersecting characteristics.

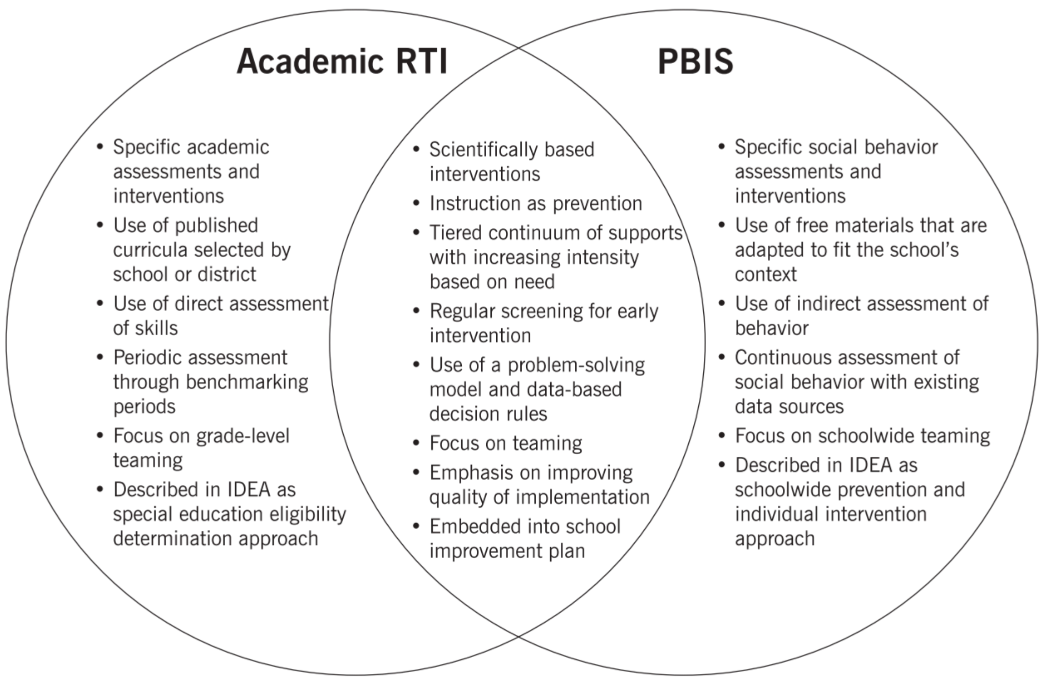

Figure 2. Similarities and differences between academic RTI and PBIS. Reprinted from "Integrated multi-tiered systems of support: Blending RTI and PBIS." By K. McIntosh and S. Goodman, 2016, New York: The Guilford Press. Copyright 2016 by The Guilford Press. Reprinted with permission.

RTI aims to inform interventions for individual students using formative assessment, tiered interventions, collaboration, and decision making based on data (National Professional Development Center on Inclusion, 2012). RTI began as a reading assessment theory in the 1980s and is now considered to be a service delivery approach (Barnes & Harlacher, 2008). RTI was applied to all academic areas and replaced the ability-achievement model of assessment (Schulte, 2016). The utilization and expansion of RTI introduced universal screening to education (Fuchs & Vaughn, 2012).

On the other hand, PBIS or PWPBS, is RTI methods applied to behavior and social difficulties (McIntosh & Goodman, 2016). PBIS aims to prevent problem behavior and increase social competence through specific interventions (Stanton-Chapman, Walker, Voorhees, & Snell, 2016). PBIS interventions are based on a three-tier model with intervention intensity increasing from Tier 1 to Tier 3 (Stanton-Chapman et al., 2016). PBIS focuses on instructional and environmental changes to influence behavior and utilizes applied behavior analysis techniques (McIntosh & Goodman, 2016).

MTSS weaves the academic focus of RTI and the behavior and social focus of PBIS into one cohesive model to best address all student needs (Figure 3). MTSS aims to provide high-quality, individualized instruction and intervention, informed by frequent progress monitoring, for all aspects of student education (McIntosh & Goodman, 2016). Data-based decision making and evidence-based practice provide the foundation for MTSS (Forman & Crystal, 2015; Stoiber & Gettinger, 2015). This model addresses education in abroad, and all-encompassing, context (McIntosh & Goodman, 2016).

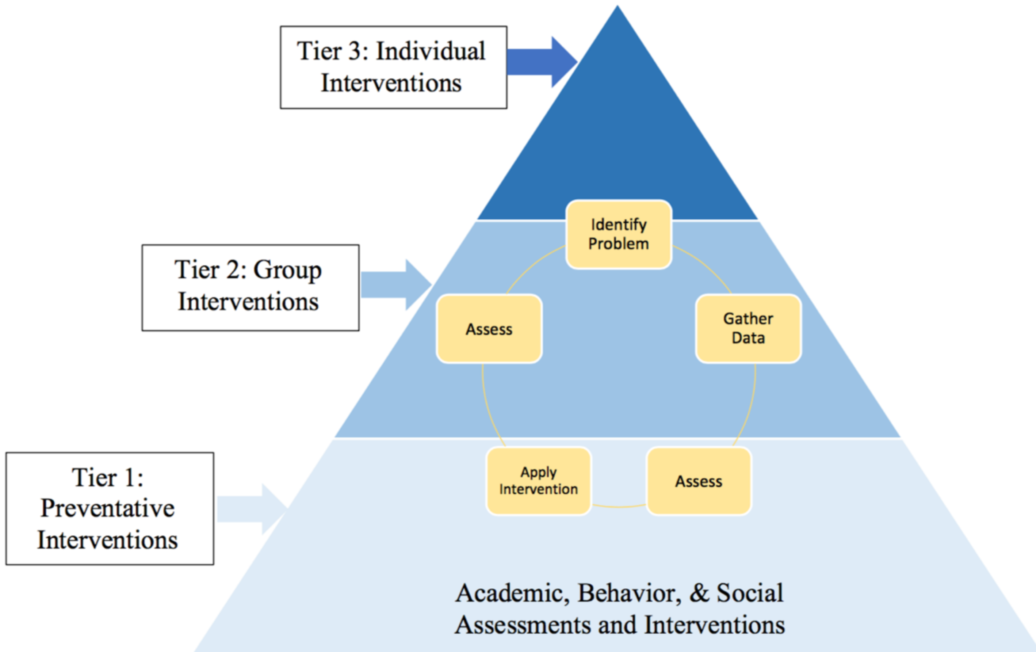

Figure 3. Multi-tiered systems of support (MTSS) model.

This approach does not merely apply RTI and PBIS assessment and intervention methods simultaneously, and instead carefully and systematically integrates these methods in the most efficient (McIntosh & Goodman, 2016) and practical (Stewart, Benner, Martella, & Marchand-Martella, 2007) manner. MTSS does so by applying a problem-solving process that includes identifying a problem, gathering data, assessing functioning, applying interventions, and assessing the effectiveness of the interventions (Lexia Learning, 2018). The utility of MTSS is dependent upon the identification of specific and measurable definitions of a problem (Colorado Department of Education, 2016). The problems also must be matched to a desired outcome or performance and decision rules signaling the need for more focused interventions (Colorado Department of Education, 2016).

MTSS asserts that prevention for all is more effective and efficient than individualized interventions (McIntosh & Goodman, 2016). Tier 1, the universal support tier, aims to maximize student success in all areas (McIntosh & Goodman, 2016). Tier 1 interventions include the following six principles: (1) focus on big ideas, (2) use obvious strategies, (3) include scaffolding, (4) strategically integrate content, (5) link new information to previously learned information, and (6) review student skills and understanding (Coyne, 2007). For example, all students are taught the meaning of respect and how to use this skill in various scenarios by reading books, discussing situations, and by reminders through teacher prompts (e.g., "That was not a respectful way to speak to your classmate, next time ask them to please speak quiet down"). Tier 2, the group intervention tier, aims to provide efficient support with cross-content interventions to groups of students (McIntosh & Goodman, 2016). Often student groups are formed by academic needs and behavior/social interventions are added as needed (McIntosh & Goodman, 2016). For example, a group of students is formed who are behind grade-level in reading and multiple students are engaging in avoidant behavior during reading time. This group was then taught additional reading interventions and strategies to use when becoming frustrated or embarrassed by their reading difficulties to decrease avoidant behavior. Finally, Tier 3, the individual intervention tier, aims to provide individualized and intensive interventions if interventions in the other tiers are not sufficient (McIntosh & Goodman, 2016). The importance of integrating academic and behavior/social interventions is most crucial in Tier 3 because separating academic and behavior/social interventions can cause action plans not to consider all of the student's needs and deny the student access to necessary interventions (McIntosh & Goodman, 2016).

The inclusion and integration of multiple system-level approaches, including school-family partnerships (Haines et al., 2017), wraparound support (Coffey et al., 2018), parent management training (August, Piehler, & Miller, 2018), mental health support (Orlando et al., 2018), and school drop-out prevention (Chu et al., 2018) has improved student educational and behavior outcomes. The nature of MTSS optimizes school resources and increases the sustainability of interventions leading to increased or maintained funding (McIntosh, Bohanon, & Goodman, 2010; McIntosh, Horner, & Sugai, 2009).

MTSS' comprehensive, evidence-based, and efficient nature has led to its widespread adoption in school settings (August et al., 2018). Contemporary classification models of school absenteeism are, primarily, comprehensive and multitiered to include numerous relevant contextual factors (Kearney, 2016). Recently, MTSS has been applied to school absenteeism. The following section describes the application of MTSS to school absenteeism.

MTSS and school absenteeism. Multiple comprehensive models of school absenteeism have paved the way for the application of MTSS. Reid (2003, 2005, 2012) worked on specifying the individual and instructional factors related to school absenteeism in a comprehensive preventative model. This model categorizes students into groups based on their risk of displaying attendance problems (i.e., none, some, minor, and persistent) and assigns school personnel to each group (Reid, 2003). Similarly, Chu and colleagues (2018) identified students at risk of displaying absenteeism and assigned school counselors to track their attendance and report factors placing them at increased risk. Kearney (2008) proposed an interdisciplinary model that categorizes students into increasingly complex groups based on specific youth psychopathology, family, peer, and school risk factors and assigns interventions to each group. Lyon and Cotler (2009) proposed a multitiered model that categorizes students into levels based on microsystem, mesosystem, and exosystem influences and assigns interventions to each level. Similarly, Rodríguez and Conchas (2009) proposed a community-based model aimed at interventions that address school-community involvement. These comprehensive models improved the conceptualization of school absenteeism but continued to lack utility due to their abstract and theoretical nature (Kearney, 2016).

Kearney and Graczyk (2014) were the first to apply MTSS principles to models of school absenteeism. This model aimed to organize evidence-based assessment and intervention strategies into three tiers (Figure 4). Each tier has a specific focus based on the severity of one's school absenteeism: (1) Tier 1 focuses on the enhancement of individual functioning and prevention of absenteeism difficulties for all students, (2) Tier 2 focuses on emerging difficulties for students with mild to moderate school absenteeism, and (3) Tier 3 focuses on addressing difficulties of students with severe school absenteeism (Kearney, 2016). Specific interventions are matched to each tier to decrease the burden of identifying interventions for each student for school personnel.

Tier 1 interventions focus on improving school climate, safety, health, parent-school involvement, or student-school involvement (Kearney, 2016). Tier 1 interventions may include informing students and their families about specific attendance policies, resources aimed to decrease absences, and guidelines for keeping a student home when they are ill. Interventions may also ensure attendance is monitored regularly, provide parents access to up to date attendance reporting, notify parents immediately if a student is marked absent, and assign school personnel to monitor areas where students often leave school or skip class.

Tier 2 interventions include peer or teacher mentoring programs, individual or group therapy addressing anxiety symptoms, or psychologically treating non-anxiety-based absenteeism (Kearney, 2016). Tier 2 interventions may include encouraging parents to engage in regular contact with school officials, monitoring attendance at each class period, beginning school reintegration, referring to medical professionals, implementing morning schedules to decrease barriers to timely attendance, supervising transitions throughout the day to decrease skipping, utilizing established resources, or assigning a student mentor.

Finally, Tier 3 interventions include alternative schools, case management, or special education programs (Kearney, 2016). Tier 3 interventions may include addressing difficulties within the family, improving communication and problem-solving skills, addressing psychological or medical needs, pursuing routes to preserve academic progress, or providing social skills aimed at decreasing negative behaviors.

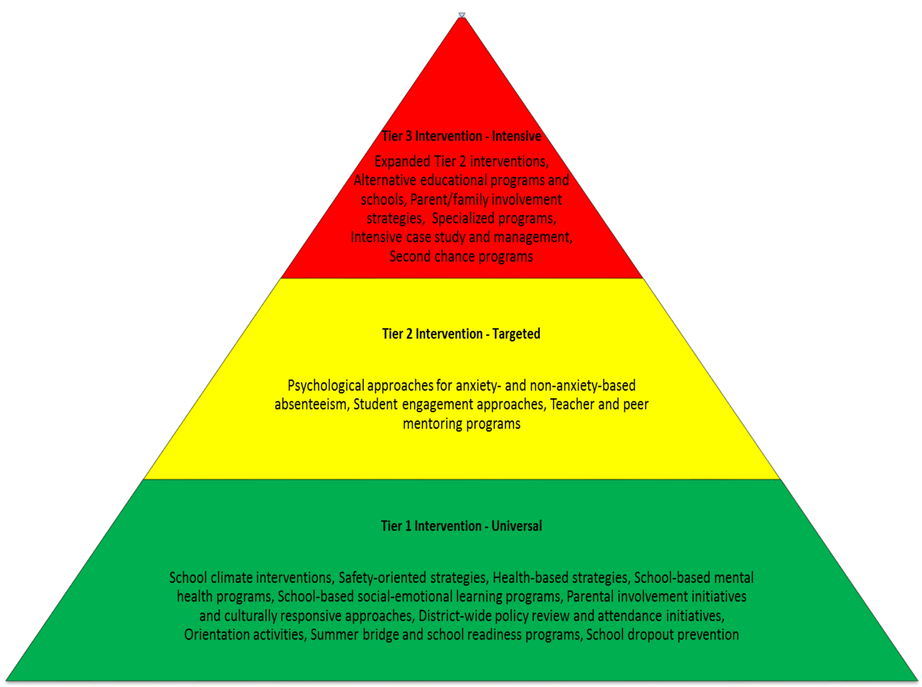

Figure 4. A multitier model for problematic school absenteeism. Reprinted from "Managing school absenteeism as multiple tiers: An evidence-based and practical guide for professionals"

by C. A. Kearney, 2016, New York: Oxford University Press. Copyright 2016 by the Oxford University Press. Reprinted with permission.

Recent research has continued to demonstrate the value of applying MTSS models to school absenteeism. Specifically, schools that implement MTSS with greater fidelity have lower levels of school absenteeism than schools with less fidelity (Freeman et al., 2016). School districts are also beginning to include attendance measures in MTSS models. For example, one school district explicitly included attendance monitoring in the application of MTSS to improve student attendance, behavior, and academic performance (Coffey et al., 2018). Ingul, Havik, and Heyne (2018) aimed to identify early signs and risk factors of emerging school attendance difficulties and pair identified signs and/factors with interventions applied in tiers one or two. Similarly, Chu and colleagues (2018) developed an early identification system for schools that identify youth who miss more than five days of school or who are at risk of developing school absenteeism based on a range of risk factors.

MTSS has been well applied to common academic and behavioral problems but lacks empirical support of application to problematic school absenteeism. School districts need specific guidelines for applying MTSS to school absenteeism. Even more so, due to recent changes to federal and state laws that encourage the utilization of attendance monitoring systems to require districts to work toward decreasing school absenteeism (Department of Education, 2016). The identification of a specific and measurable definition of problematic school absenteeism and specific demarcations of severity level among the tiers is necessary to apply MTSS to problematic school absenteeism successfully.

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The current study aimed to address this need by supporting a more precise definition of problematic school absenteeism and identifying specific subgroups of youth at various levels of risk for displaying problematic school absenteeism based upon family environment and youth psychopathology. This study utilized MTSS as a theoretical framework. Study one utilized MTSS to identify more pristine distinctions of problematic school absenteeism among the tiers. In studies two and three, family environment and youth psychopathology risk factors are analyzed to distinguish youth with problematic school absenteeism in each of the MTSS tiers. Results have important implications for increasing the clarity and utility of early assessment and intervention methods for youth with problematic school absenteeism, particularly methods that utilize the MTSS framework. Doing so, will provide school-based personnel with specific guidelines for assessing problematic school absenteeism, categorizing students into tiers based on their level of severity, and employing interventions specific to each tier.

The following section reviews relevant problematic school absenteeism risk factors with a focus on family environment and youth psychopathology variables that are most pertinent to the current study.

Risk factors

Problematic school absenteeism is related to many risk factors specific to the individual, family, community, peers, and school environment. Youth with problematic school absenteeism commonly display multiple risk factors leading to an increase in severity and complexity in treatment (Kearney, 2016). An extensive, though not comprehensive, list of related risk factors is in Table 5. Youth psychopathology and family environment risk factors most relevant to the current study are described in detail below.

Table 5

Proximal and Distal Factors Related to Problematic School Absenteeism

Factors	
Key child factors	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
	Personality traits and attributional styles
	Poor health or academic proficiency
	Pregnancy

	Problematic relationships with authority figures
	Race and age
	Trauma
	Underdeveloped social and academic skills
Key parent factors	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
Key family factors	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 (divorce, illness, unemployment, moving)
	Transportation problems
Key peer factors	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 for alluring activities outside of school such as drug use
	Victimization from bullies or otherwise
Key school factors	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

Key community factors	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. Reprinted from "An Interdisciplinary Model of School Absenteeism in Youth to Inform Professional Practice and Public Policy," by C.A. Kearney, 2008, *Educational Psychology Review, 20,* p. 259. Copyright 2008 by Springer Science + Business Media, LLC. Reprinted with permission.

Youth psychopathology. Twenty percent of school-aged youth have mental health difficulties that impact their academic achievement (Macklem, 2014), with some districts reporting rates as high as 50% (Duchnowski, Kutash, & Friedman, 2002). The negative impact of mental health difficulties on youth academic achievement has been identified in students as young as the first grade (Guzman et al., 2011). Lack of access to community-based mental health services has caused the mental health care of school-aged youth to fall on their school (Kathleen Ries Merikangas et al., 2011). To address increasing mental health concerns some schools have slowly begun to implement voluntary mental health screenings (Stiffler & Dever, 2015). Approximately one-third of mental health concerns identified by these screenings have been previously unidentified (Husky, Kaplan, et al., 2011). The implementation of MTSS and its comprehensive approach to addressing student needs has drawn attention to the need for early assessment of student mental health difficulties (Garzona et al., 2018).

Despite the adoption of MTSS, schools are slow to implement universal mental health screenings due to concerns about their ability to meet student needs and the lack of clearly identified treatment, referral, and follow-up protocols (Garzona et al., 2018; Husky, Sheridan, McGuire, & Olfson, 2011). Further, schools do not have specific guidelines for youth psychopathology as related to the MTSS tiers and therefore lack the ability to appropriately categorize student mental health difficulties and provide interventions (August et al., 2018). Study three of the current study aimed to address this problem by identifying the most relevant youth psychopathology risk factors among youth with problematic school absenteeism and categorizing students into the MTSS tiers based on their level of severity.

Results of the current study provide school-based personnel with specific guidelines for the interpretation of early absenteeism and youth mental health screening data, thereby allowing students to efficiently be categorized into one of the MTSS tiers for intervention. Youth psychopathology variables commonly included in school-based screeners (Stiffler & Dever, 2015), often endorsed by youth with problematic school absenteeism, and most relevant to the current study are detailed below.

Common internalizing and externalizing symptoms and disorders are present in youth with problematic school absenteeism. More youth with school absenteeism (80%) endorse at least one somatic symptom than youth with only an anxiety disorder (50%; Crawley et al., 2014; Honjo et al., 2001). Common somatic symptoms endorsed by youth with school absenteeism include stomach, head, back, joint, or muscle pain as well as sweating, nausea, blurred vision, breathing difficulties, inability to speak, and difficulty swallowing (Ek & Eriksson, 2013; Kearney, 2001).

Internalizing disorders often diagnosed in youth with problematic school absenteeism include anxiety, depression, somatic, and social withdrawal symptoms (Merrell, 2008). Youth with school absenteeism have higher rates (52-54%; McShane, Walter, & Rey, 2001) of internalizing disorders than the worldwide prevalence rate (3-7%; Finning et al., 2017). Common internalizing diagnoses in youth with school absenteeism include major depressive disorder, social anxiety disorder, generalized anxiety disorder, and separation anxiety disorder (Egger et al., 2003; Maynard et al., 2015; Wimmer & Milwaukee, 2010; Wood et al., 2012). Youth with school absenteeism also have high rates of comorbidity among internalizing diagnoses (Essau, 2003; Hankin et al., 2016). The presence of comorbid diagnoses and increased somatic symptoms complicates treatment leading to decreased treatment outcomes (Maynard et al., 2015).

Externalizing disorders include lack of control of one's emotions, cognitions, or behaviors and include aggression, hyperactivity, and antisocial symptoms (Merrell, 2008). Common externalizing symptoms endorsed by youth with school absenteeism include verbal and physical aggression, noncompliance, tantrums, lying, refusal to move, clinging, or hiding symptoms (Kearney, 2001). Externalizing symptoms are a more salient predictor of youth problematic school absenteeism behavior than internalizing symptoms (Ingul, Klöckner, Silverman, & Nordahl, 2012).

Youth with school absenteeism have higher rates of externalizing disorders (8-80%; Kearney & Albano, 2004; Maynard et al., 2015) than the worldwide prevalence rate (3-6%;

Merikangas, Nakamura, & Kessler, 2009). Common externalizing diagnoses in youth with school absenteeism include oppositional defiant disorder, conduct disorder, and attention deficit hyperactivity disorder (Kearney & Albano, 2004; Wood et al., 2012).

Family environment. Family environment have been found to impact youth cognitive development, behavioral problems, and health throughout their lives, including as they transition to academic environments and adulthood (Lee & McLanahan, 2015; Magnuson & Berger, 2009; Morrongiello & Corbett, 2013; Osborne & McLanahan, 2007; Sturge-Apple, Davies, & Cummings, 2010). Further, school-based interventions, particularly mental health interventions, are the most effective when the entire family is included (Shucksmith, Jones, & Summerbell, 2010).

The comprehensive approach of MTSS calls for the inclusion of entire families at all three tiers to improve academic and behavior/social interventions (Kelly, Rossen, & Cowan, 2018; McCart, Wolf, Sweeney, & Choi, 2009). Tier 1 interventions directed at the entire family may include informing families about the services available, introducing school personnel and their role in student education or health, decreasing cultural and language barriers, and increasing communication (Kelly et al., 2018). Tier 2 interventions may include structuring daily or weekly communication between families and relevant school personnel, clearly informing parents of the services their child is receiving, their progress, and the formal special education referral process, or engaging families in networks of support with other families, school-based groups, or community groups (Kelly et al., 2018). Finally, Tier 3 interventions should work to further involve the family in daily communication, ensure they are connected to community mental health providers, involve them in school-based therapeutic services, and encourage families to include outside providers or trusted individuals who can assist them (Kelly et al., 2018). The inclusion of families in MTSS is not just beneficial for the efficacy of interventions, but it is also beneficial for the MTSS problem-solving process. In order to adequately define and identify a problem in the MTSS problem-solving process the function of the behavior must be identified. Understanding a youth's family environment and the impact of that environment to one's academic, behavioral, or social functioning is crucial for the efficacy of MTSS interventions.

Despite the well-documented impact family environment has on youth functioning and academic achievement (Morrongiello & Corbett, 2013), schools often do not involve families in the MTSS process unless involvement is legally required due to a lack of resources and concerns about their ability to meet family needs (Kelly et al., 2018). Further, there is a lack of research directly linking the family environment to problematic school absenteeism. Study two of the current study aimed to address these problems by identifying the most relevant family environment risk factors among youth with problematic school absenteeism and categorizing students into the MTSS tiers based on their level of severity. Results of the current study provide school-based personnel with specific guidelines for the interpretation of early absenteeism and family environment screening data, thereby allowing students to efficiently be categorized into one of the MTSS tiers for intervention. Results of the current study also add to the relatively small literature base linking family environment to problematic school absenteeism and provide family-based mental health providers with profiles of families at high risk of having a youth with problematic school absenteeism. Common risk factors among the family environments of youth with problematic school absenteeism are reviewed below.

Families are conceptualized as dynamic systems in which all relationships and subsystems influence one another (Lindblom et al., 2017). Several types of family dynamics have been linked to school attendance problems. First, enmeshed families display extreme closeness, emotional dependency, over-involvement, and loyalty to the family with a lack of developmentally appropriate autonomy (Berryhill, Hayes, & Lloyd, 2018). Enmeshed families often have high levels of family dysfunction and lack appropriate boundaries, communication, roles, and flexibility (Berryhill et al., 2018; Waldron, Shrier, Stone, & Tobin, 1975). Relationships in enmeshed families are likely to be insecure and marked by internalizing and externalizing symptoms (Davies, Cummings, & Winter, 2004). Youth in enmeshed families are more likely to display internalizing symptoms than youth in other types of families (Barber & Buehler, 2006; Yahav, 2002). Youth in these families have been thought to display problematic school absenteeism due to over dependency, overprotection, or hostility (Kearney & Silverman, 1995). Higher levels of internalizing symptoms among youth in enmeshed families may also impact youth problematic school absenteeism. For example, one in an enmeshed family may not attend school due to increased anxiety associated with separating from their family or an inability to manage daily tasks without the assistance of their family.

Second, conflictive families display a lack of intimacy and emotional expression in addition to high rates of conflict and hostility among family members (Chen, Wu, & Wei, 2017; Makihara, Nagaya, & Nakajima, 1985). Youth in families with high levels of conflict are more likely to have adjustment difficulties particularly for female youth (Jaycox & Repetti, 1993). High conflict families living in violent communities are at increased risks youth to display symptoms of depression and anxiety and engage in risk-taking behaviors particularly for male youth (Bradley et al., 2010). Youth in these families display absenteeism due to continued conflict (Kearney & Silverman, 1995). High levels of conflict, risk-taking behaviors, adjustment difficulties, hostility, and depression and anxiety among youth in conflictive families may also impact youth problematic school absenteeism. For example, one in a conflictive family may not attend school due to concerns for conflict in the home when they are not present, prioritizing risk-taking behaviors like skipping school, or an inability to manage their anger, depression, or anxiety.

Third, detached families display a lack of involvement with or attention to the needs of family members (Weiss & Cain, 1964). Detached families are characterized by high levels of interparent withdrawal and parental invasiveness couples with low levels of hostility, emotional availability, cooperation, cohesiveness, competition, and ability to relate to children in the family (Sturge-Apple et al., 2010). Youth in detached families are most likely to display externalizing symptoms than youth in other types of families and were at an increased risk for displaying internalizing symptoms (Lindblom et al., 2017; Sturge-Apple et al., 2010; Yahav, 2002). Detached families also endorse low family cohesion, often lack emotion regulation skills, and report insecure relationships with their family members (Davies et al., 2004; Lindblom et al., 2017; Yahav, 2002). Youth in these families display absenteeism due to a lack of vigilance about youth activities or problems (Kearney & Silverman, 1995). High levels of externalizing symptoms, internalizing symptoms, insecure relationships, withdrawal and low levels of cooperation, cohesiveness, and emotional regulation skills may also impact youth problematic school absenteeism. For example, one in a detached family may not attend school due to concerns lack of concern for family consequences, behavioral problems at school leading to noncompliant behaviors like skipping school, or a lack of cooperation with school rules.

Fourth, isolated families are characterized by minimal, if any, contact with people outside of the family (Wahler, 1980). These families are unlikely to seek help from anyone outside of the immediate family (Garbarino, 1977). Isolated families are at increased risk for child maltreatment particularly when there are high levels of stress and increased family dysfunction

(Gracia & Musitu, 2003; Tucker & Rodriguez, 2014). Youth in these families display absenteeism due to a lack of integration in their community and lack of engagement outside of the family (Kearney & Silverman, 1995). Low levels of social interaction and support coupled with high levels of stress, dysfunction, and child maltreatment may also impact youth problematic school absenteeism. For example, one in an isolated family may not attend school due to lack of support or encouragement outside of the family, concerns for stress or dysfunction in the home when they are not present, or to conceal child maltreatment.

Fifth, healthy families are characterized by demonstrating healthy and adaptive functioning and lacking the common themes found in the previous family types (Kearney & Silverman, 1995). Health families often have adequate or high levels of cohesion that is associated with a decreased risk for internalizing and externalizing problems particularly for adolescents (Barber & Buehler, 2006). Despite a family being healthy youth may still display absenteeism (Kearney & Silverman, 1995). For example, one in a healthy family may not attend school due to youth mental health, avoidance of social situations or schoolwork, or succumbing to peer pressure.

There is overlap in the distinctions between the family types and the common characteristics within each type. This overlap creates mixed families who display characteristics of two or more of the previous family types leading to various causes of a youth's absenteeism (Kearney & Silverman, 1995). Mixed families may display a primary characteristic of a particular family type while still displaying characteristics of one or more additional types. Families of youth with problematic school absenteeism often are categorized as mixed families (Kearney & Silverman, 1995). One in a mixed family may not attend school due to enmeshment with their family and increased conflict due to a lack of clear boundaries or social isolation from the outside world and detachment from one another within the family (Kearney & Silverman, 1995).

Current study

The current problematic school absenteeism literature has many limitations. First, and foremost, there is a lack of an agreed-upon definition of problematic school absenteeism in research or school districts (Jimerson, Burns, & VanDerHeyden, 2016; Lyon & Cotler, 2007). Currently used definitions range from 1% to 40% of full school days missed (Berg et al., 1993; Egger et al., 2003) and may include functional criteria such as impact to the student's individual, family, or academic functioning (Kearney, 2008). Inconsistent definitions of problematic school absenteeism have led to problems within the literature including complicated or counteracting interpretations of findings, difficulty identifying the severity of the problem, and problems identifying solutions (David et al., 2018; Kearney & Graczyk, 2014; Maynard et al., 2015). Lack of consistent definitions has also led to problems with the utility of problematic school absenteeism research for mental health professionals including complicated, and often counteracting, early identification systems and an inability to access effective treatments or interventions (David et al., 2018; Maynard et al., 2015). Further, current definitions of problematic school absenteeism in the literature lack utility for school personnel and are not used by school districts (Attendance Works, 2016; National Center for School Engagement, 2005; Schanzenbach et al., 2016; Spruyt et al., 2016; U.S. Department of Education Office of Safe and Drug-Free Schools, 2007). MTSS and other data-based program modification models require specific and measurable definitions of problems and levels of severity.

Second, the current school absenteeism research lacks attention to the impact of family environment and youth psychopathology factors on school absenteeism. Despite the well-documented impact family environment has on youth functioning and academic achievement (Morrongiello & Corbett, 2013), schools often do not involve families in the MTSS process unless involvement is legally required due to a lack of resources and concerns about the school's ability to meet family needs (Kelly et al., 2018). Further, there is a lack of research directly linking the family environment to problematic school absenteeism. Available research has utilized only clinical populations (Bahali, Tahiroglu, Avci, & Seydaoglu, 2011) and worked to identify family process variables (G. Melvin, Carless, Melvin, Tonge, & Newman, 2015), subtypes of families of youth who refuse school (Kearney & Silverman, 1995), or the function of one's school refusal behavior (Kearney & Silverman, 1996). Similarly, youth with problematic school absenteeism often display internalizing and externalizing symptoms (Crawley et al., 2014; Park et al., 2015) and diagnoses (Kearney, 2016). Research has well-documented the negative impact of mental health difficulties to academic achievement (Macklem, 2014), the lack of access to mental health services, the increased need for mental health care in school (Kathleen Ries Merikangas et al., 2011), and the efficacy of school-based universal mental health screenings (Stiffler & Dever, 2015). Despite this, schools are slow to implement universal mental health screenings due to concerns about their ability to meet student needs and the lack of clearly identified treatment, referral, and follow-up protocols (Garzona et al., 2018; Husky, Sheridan, et al., 2011).

Third, populations and sample sizes limit current school absenteeism research. The majority of the research in this area focuses on clinical populations with small sample sizes and lack the inclusion of minority groups (Gill & Redwood, 2013; Haight, Kearney, Hendron, & Schafer, 2011; Kearney & Albano, 2004; Low, Cui, & Merikangas, 2008). This limitation is problematic for the generalization of findings, selection bias, and potential for false-positive findings (Low et al., 2008).

Finally, traditional parametric statistical approaches limit the findings of school absenteeism research. Traditional parametric approaches lack the ability to simultaneously analyze the role of multiple risk factors or different types of risk factors (Rizzo, Chen, Fang, Ziganshin, & Elefteriades, 2014; H. Zhang & Singer, 2010), efficiently address missing data (Kang, 2013), and decrease the adverse effects of multicollinearity (Yoo et al., 2014). These traditional approaches have been utilized to identify relevant risk factors but have been unable to reveal the interactions between these risk factors (Kiernan, Kraemer, Winkleby, King, & Taylor, 2001). The identification of high-risk groups or individuals is essential for the application of MTSS and may decrease the treatment costs associated with long-term symptoms (Bates, Saria, Ohno-Machado, Shah, & Escobar, 2014).

The current study aimed to address this need by supporting a precise definition of problematic school absenteeism and identifying specific levels of severity based on family environment and youth psychopathology risk factors to inform multi-tiered systems of support (MTSS). MTSS provided the theoretical framework to identify more pristine distinctions of problematic school absenteeism among the tiers.

Study one reviewed the current literature and utilized MTSS as a theoretical framework to identify more pristine distinctions of problematic school absenteeism among the tiers. Results have important implications for increasing the clarity and utility of early assessment and intervention methods for youth with problematic school absenteeism, particularly methods that utilize the MTSS framework. Results provide school-based personnel with specific guidelines for assessing problematic school absenteeism, categorizing students into tiers based on their level of severity, and employing interventions specific to each tier.

Study two of the current study aimed to address these problems by identifying the most relevant family environment risk factors among youth with problematic school absenteeism and categorizing students into the MTSS tiers based on their level of severity. Results of the current study provide school-based personnel with specific guidelines for the interpretation of early absenteeism and family environment screening data, thereby allowing students to efficiently be categorized into one of the MTSS tiers for intervention. Results of the current study also add to the relatively small literature base linking family environment to problematic school absenteeism and provide family-based mental health providers with profiles of families at high risk of having a youth with problematic school absenteeism.

Study three of the current study aimed to address this problem by identifying the most relevant youth psychopathology risk factors among youth with problematic school absenteeism and categorizing students into the MTSS tiers based on their level of severity. Results of the current study provide school-based personnel with specific guidelines for the interpretation of early absenteeism and youth mental health screening data, thereby allowing students to efficiently be categorized into one of the MTSS tiers for intervention.

Studies two and three utilized ensemble analysis to identify youth at the highest risk of problematic school absenteeism (i.e., dependent variable) based on youth psychopathology and family environment risk factors (i.e., independent variables). The following section outlines ensemble analysis.

Analyses.

Ensemble analysis. Ensemble analysis is the combination of multiple algorithmic models (i.e., classifiers) to produce one model that has been applied to the data in many different ways (Berk, 2006). These nonparametric methods are often referred to as algorithmic and were based on data mining, machine learning, and statistical learning techniques (Berk, 2006; Breiman, 2001). Algorithmic models do not depend on a statistical model and, instead, aim to solve a problem directly by searching a designated dataset to identify the single best model (Dietterich, 2007). For example, if the goal is to identify which high school students are most likely to drop out of school, algorithmic models will solve this problem by classifying high school students and identifying the highest risk subgroup. There is mounting evidence that these models outperform standard parametric methods, primarily due to the automation of identifying interactions and non-linearities and the reduction of overestimating the model's predictive ability (Rosellini, Dussaillant, Zubizarreta, Kessler, & Rose, 2018).

Despite growing evidence supporting the performance of algorithmic models (Breiman, 2001), there are noted weaknesses. First, large amounts of data are needed to identify the best model (Dietterich, 2007). Algorithmic models applied to insufficient data would produce many different models with the same accuracy clouding the algorithms ability to identify the best model (Dietterich, 2007). Second, algorithmic models are preprogrammed to solve specific problems within a specific dataset but are unable to make adjustments to the algorithm causing it to become stuck in local optima and inaccurately identify a best-fitting model (Dietterich, 2007). Finally, these models are preprogrammed to identify a model in a training sample and will stop searching when a model that fits the data has been identified likely leading the algorithm to ignore other potential better models (Dietterich, 2007).

Ensemble analysis advances algorithmic models in many ways including the reduction or elimination of the three main problems described above. Primarily, ensemble analysis addresses these problems by averaging the models of many different algorithmic models (i.e., classifiers) to identify one model that best fits the sample (Berk, 2006; Dietterich, 2007). Each of the algorithmic models (i.e., classifiers) are also employed at many different starting points in the data to decrease bias in their application and avoid becoming stuck in local optima (Dietterich, 2007). Instead of identifying one model and stopping the search, ensemble analysis continues to identify all possible models that fit the training sample (Dietterich, 2007). Overall, ensemble analysis employs many different algorithmic models (i.e., classifiers) simultaneously to identify one model that best fits the data.

Ensemble analysis is strikingly similar to everyday decision making in that before making significant decisions consultation with others often occurs (Polikar, 2012). For example, if one was asked to choose a hotel for their vacation, it is likely that they will ask people whom they know traveled to the area or read the reviews of other travelers and take into account all of this information before making a final decision. One would not only take the advice of one person without checking other information sources. The goal of ensemble analysis is similar in that one final model is selected by evaluating the models of multiple algorithmic methods (i.e., classifiers) with similar bias and averaging the responses to reduce variance (Breiman, 1998; Kuncheva, 2002; Polikar, 2012; Woods, Philip Kegelmeyer, & Bowyer, 1997; Zhou, 2009).

Classifier fusion is the method in which classifiers are combined (Polikar, 2012). In general, classifier fusion assumes each classifier (i.e., algorithm) is equally experienced and, therefore, is given equal weight (Kuncheva, 2002). Classifiers are considered to be competitive as only one model will be selected from one classifier (Kuncheva, 2002). There are many different classifier fusion methods including random forests, bagging, boosting, and stacking approaches that are commonly used in ensemble analysis (Polikar, 2012; Zhou, 2009; Figure 5). Each of these methods is reviewed below.

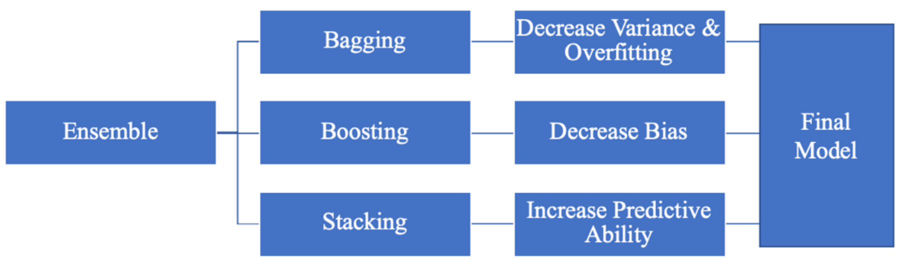

Figure 5. Components of ensemble analysis.

Bagging. Bootstrap Aggregation or bagging is the first and most simple ensemble method (Breiman, 2004; Zhang & Ma, 2012). Bagging is a simple algorithm aimed to decrease variance in the model and overfitting (DeFilippi, 2018). Bagging follows these steps, (1) select a random sample of *n* (number of observations) with replacement data, (2) employ a large number of classification trees from bootstrap samples, (3) do not prune the trees, (4) total the number of times each case is classified in each category, and (5) assign each case to the category with the largest total (Berk, 2006). In other words, each case is assigned to the category it most frequently appears in (i.e., majority voting) among the unpruned classification trees (Zhou, 2009; Figure 6).

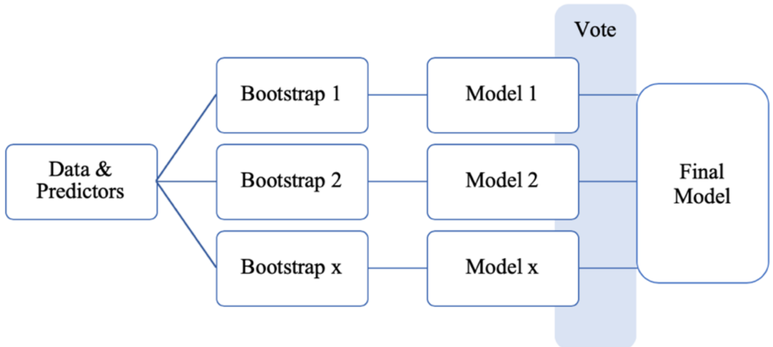

Figure 6. Bagging steps.

Bagging solves classification methods' (i.e., classification and regression tree) overfitting issues, but the final output does not provide a tree model to allow for interpretations of individual predictors as is provided by classification and regression trees (Berk, 2006). Instead, bagging is an algorithmic model (Breiman, 2001) in that bagging is not a causal model and instead, the model identifies the link between one or more inputs (Berk, 2006).

Random Forests is an algorithmic modeling procedure based on bagging algorithms. Breiman (2001) defined random forests as "a classifier consisting of a collection of tree-structured classifiers {h(x,Θk), k = 1,...} where the {Θk} are independent identically distributed random vectors, and each tree casts a unit vote for the most popular class at input x." (p. 6). In other words, random forests are based upon a random sample of predictors differentiating this procedure from bagging which uses all predictors. Random forests follow these steps (1) employ a large number of trees from bootstrap samples, (2) before splitting each node, select a random sample of predictors, (3) split the node from the random sample of predictors only, (4) repeat until stopping criteria is met, (5) do not prune the trees, (6) total the number of times each case is classified in each category, and (7) assign each case to the category with the largest total (Berk, 2006).

Boosting. Boosting refers to a group of algorithms including AdaBoost, the most famous boosting algorithm, that aims to decrease bias in the model (DeFilippi, 2018; Freund & Schapire, 1997). Similar to other methods, boosting is a forward stage wise additive model but it expands upon this process by using the entire data set at each stage or split (Berk, 2006). In general, boosting takes a weak algorithm, “boosts” its performance, and creates a strong algorithm (Berk, 2006; Freund & Schapire, 1997). Boosting follows these steps (1) all training examples are assigned equal weight, (2) a base learner is generated from the base learning algorithm, (3) all models are tested using the training examples, (4) the incorrectly classified examples are weighted at an increasing level, (5) another base learner is generated from the training data set using the base learning algorithm, (6) the process is completed for multiple rounds, (7) the final learner is selected by a weighted vote of the base learners (Zhou, 2009; Figure 7). Boosting outputs are similar to bagging outputs and include confusing tables, error rates, and predicted classifications (Berk, 2006). In other words, boosting combines inadequate algorithms to create an accurate prediction (Freund & Schapire, 1997).

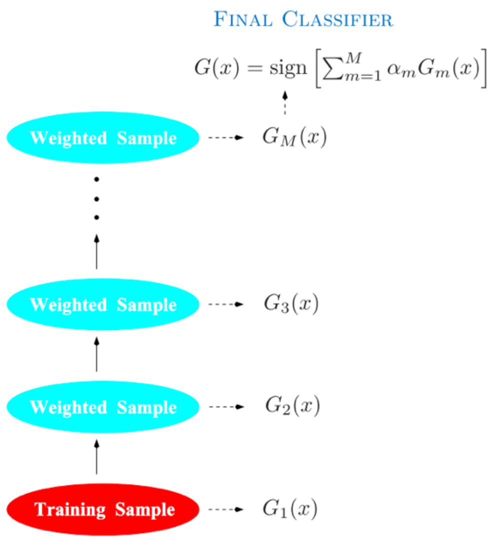

Figure 7. Schematic of AdaBoost. Classifiers are trained on weighted versions of the dataset, and then combined to produce a final prediction. Reprinted from "The elements of statistical learning: Data mining, inference, and prediction" by T. Hastie, R. Tibshirani, & J. Friedman, 2009, New York: Springer Series in Statistics. Copyright 2009 by the Springer Series in Statistics. Reprinted with permission.

Stacking. Stacked generalization or stacking aims to improve the predictive ability of the classifier by blending all predictions into one final prediction (DeFilippi, 2018). Stacking is an improved, and more sophisticated, form of cross-validation (Wolpert, 1992). Stacking differs from bagging and boosting in that it weights nonconforming models differently based on the models performance in reference data instead of relying on agreement (i.e., voting) and it combines different types of classifiers that are likely, not correlated instead of combining similar classifiers (Healey et al., 2018; Priore, Ponte, Puente, & Gómez, 2018).

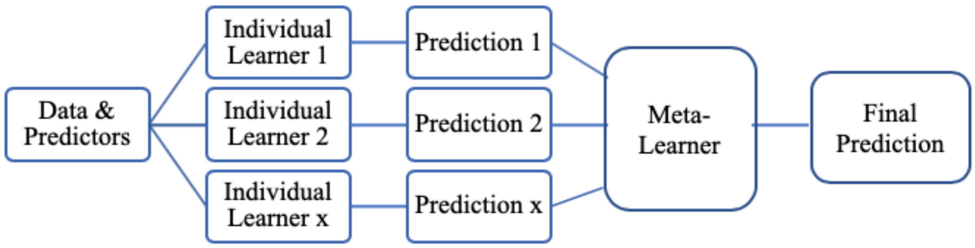

Figure 8. Stacking steps.

Stacking occurs in the following steps (1) individual learners are created from the training data with different algorithms, (2) each learner identifies a prediction, (3) the predictions are combined in a new dataset, the meta-learner, and (4) the final model is fit to the new dataset (DeFilippi, 2018; Ting & Witten, 1997; Zhou, 2009; Figure 8).

Analyses Included in Ensemble Analysis. Ensemble analysis can include many different statistical methods based upon the aim of the study or the needs of the researcher. The present study will utilize Chi-square adjusted interaction detection (CHAID), support vector machines, and neural network analyses. Each of these analyses are described in detail below.

Chi-Square Automatic Interaction Detection. Chi-square automatic interaction detection (CHAID), a type of automatic interaction detection (Fielding & O'Muircheartaigh, 1977), is a parametric recursive partitioning method (Lin, Noe, & He, 2006). CHAID narrows a population into homogenous subgroups based on a common categorical characteristic (i.e., risk factor; Kass, 1980). CHAID can be thought of as describing or depicting interactions among multiple risk factors by producing a multilevel output resembling a tree (Figure 9; Lin et al., 2006).

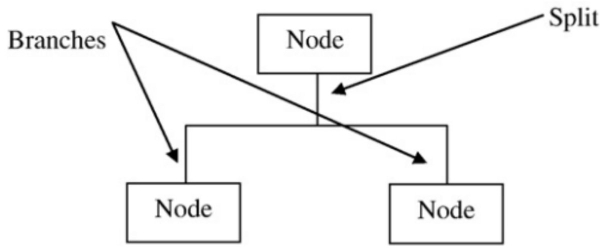

Figure 9. Key terms for classification tree analysis. Reprinted from "The relation of student behavior, peer status, race, and gender to decisions about school discipline using CHAID decision trees and regression modeling." By S. Horer, G. Fireman, & E. Wang, 2010, Journal of School Psychology. Copyright 2010 by the Society for the Study of School Psychology. Reprinted with permission.

CHAID's algorithm requires a categorical dependent variable in order to begin the process (Song & Lu, 2015). Groups and subgroups are referred to as a "node" (Figure 9; Lemon, Roy, Clark, Friedmann, & Rakowski, 2003). The tree starts with the entire sample in a "parent node" and is split into branches forming new "child nodes" (Byeon, 2018). Independent variables are referred to as a "splitting variable" or "input variable" and can be either categorical or continuous (Lemon et al., 2003; Song & Lu, 2015). The CHAID algorithm utilizes chi-squared tests as the "splitting criterion" to determine the most accurate division at each split without restricting the number of branches (Horner, Fireman, & Wang, 2010). Branches are formed to create homogenous nodes that are exhaustive and differ significantly from other nodes in the branch based on the chi-square statistic (Kass, 1980; Merkle & Shaffer, 2011). The process continues until stopping rules are met. Stopping rules ensure the tree does not become too large or continue to split despite lack of statistical interpretability (Lemon et al., 2003). CHAID's algorithm employs four stopping rules (1) the p-value of the split must not exceed the identified maximum (i.e., 5%); (2) the number of levels must not exceed the identified maximum; (3) the minimum number of cases included in a parent node must be met; (4) the minimum number of cases to be included in a child node must be met (Ritschard, 2010). CHAID is able to efficiently handle missing data by classifying missing values as a distinct category that can be analyzed in the same way as other categories (Song & Lu, 2015).

Neural Networks. Neural networks is a classification technique that utilizes a set of algorithms to recognize patterns in data (Biem, 2014; Skymind, 2019). The goal of neural networks are to efficiently cluster and classify unlabeled data for interpretation (Skymind, 2019). Neural networks are based upon connectionist models that model parts of human perception, cognition, behavior, learning processes, and memory (Hong, 1988). Neural networks are categorized by the following four concepts (1) neuron model describes how one unit in the network causes an output and describes the units role in the larger network, (2) architecture maps the connection between units, (3) data encoding policy describes how input data are represented in the network, (4) training algorithm estimates the optimal weights of each unit (Biem, 2014). Neural networks is best used for (1) modeling nonlinear systems, (2) data that will continue to be available, (3) models that constantly need updated, (4) unexpected changes in input data, and (5) situations that do not prioritize models that are easily interpretable (MathWorks, 2016).

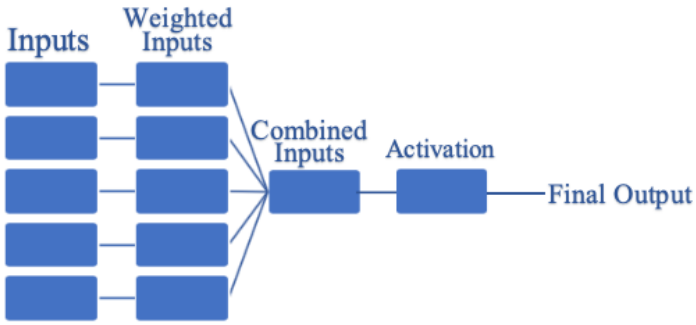

Figure 10. Neural network steps in a single node.

Neural networks' algorithms use the following steps (Figure 10), (1) inputs are weighted to increase or decrease the importance of each input, (2) a node combines data from the weighted inputs and assigns significance to each input, (3) the algorithm determines if the node should progress by either activating or not activating the node (4) if the node is activated, a final output is identified (Skymind, 2019). Each node can be compared to a neuron in that they are either activated or not based on the relevance of the node to overall data (Skymind, 2019).

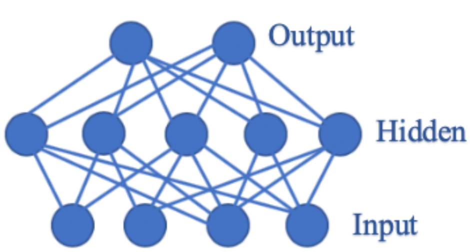

Figure 11. Neural network row.

Each node is then compared to other nodes in the layer based upon the combined weight and a final output is selected (Figure 11; Skymind, 2019). One row's output becomes the next row's input and the process continues until all rows have been presented to the algorithm (Skymind, 2019). Each row of nodes includes an input layer, hidden layer, and output layer (Shah, 2017). Neural networks can include up to three layers of nodes.

Support Vector Machines. Support vector machines (SVM) is a learning machine that generalizes information learned from training data to make predictions for novel data (Campbell & Ying, 2011). To classify data, SVM finds the hyperplane that separates two classes of data with the best hyperplane being one with the largest margin between the classes (MathWorks, 2016). SVM relies on the principle of structural risk minimization that states "for any given classification task, with a certain amount of training data, generalization performance is solely achieved if the accuracy on the particular training set and the capacity of the machine to pursue learning on any other training set without error have a good balance" (Preuss, 2014b, pg. 2). SVM is best used with data that (1) has only two classes, (2) is nonlinearly separable and high-dimensional, and (3) requires an accurate and easy to interpret classifier (MathWorks, 2016).

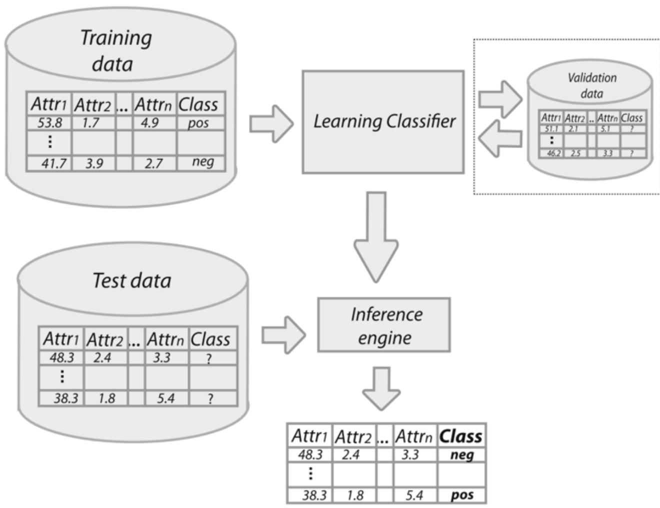

Figure 12. The classifier learns the associations between the training samples and their corresponding classes and is then calibrated on the validation samples. The resulting inference engine is subsequently used to classify new test data. The validation process can be omitted, especially for relatively small data sets. The process is subject to cross-validation, in order to estimate the practical prediction accuracy. Reprinted from “*Introduction.*” By C. Stoean & R. Stoean, 2014, in “Support vector machines and evolutionary algorithms for classification: Single or together?”. Copyright 2014 by Springer International Publishing. Reprinted with permission.

SVM uses the following steps (Figure 12), (1) during the training phase, an identified classifier (e.g., algorithm) learns with associations the training data and the output, (2) during the testing phase, the obtained inference engine uses each test sample to predict its class, (3) the accuracy of the prediction is calculated by identifying the percent of cases that were labeled correctly, (4) cross-validation estimates the predictive accuracy of the model, and (5) the generalization ability of the model is identified by averaging the test prediction accuracy over cross-validation rounds (Preuss, 2014a).

Application of Ensemble Analysis. Ensemble and similar analysis has been primarily used in hard sciences (Berk, 2006). For example, ensemble analysis has been used to predict traffic volume (Xiao et al., 2019) and examine the security of a power system (Zhukov et al., 2019). Similarly, ensemble analysis is beginning to be applied to social science research. Ensemble analysis has been applied to improving the accuracy of tweet translations into Arabic (Abdelaal, Elmahdy, Halawa, & Youness, 2018), predicting romantic desire among individuals participating in speed-dating (Joel, Eastwick, & Finkel, 2017), and modeling student satisfaction with humanities courses (Corduas & Piscitelli, 2017). Ensemble analysis is also gaining popularity in medical and behavioral health research. For example, ensemble analysis was used to predict the incidence of post-traumatic stress disorder diagnoses after a hurricane (Rosellini et al., 2018), predict neuroblastoma patient outcomes (Cornero et al., 2012), and model ICD-10 diagnosis from clinical data records (G. Zhang et al., 2015).

The current study used ensemble analysis to identify the best fitting model to predict specific levels of problematic school absenteeism severity based on family environment and youth psychopathology risk factors. The nonparametric nature of ensemble analysis is meant to generate hypotheses and not to test hypotheses. Therefore, the available literature addressing youth psychopathology and family environment risk factors of problematic school absenteeism informed hypotheses of study two and study three.

Hypotheses. Study one reviewed the current literature to identify more pristine distinctions of problematic school absenteeism among the MTSS tiers. Hypothesis one is that 1% of full school days missed (e.g., 1.8 school days) will be the best cutoff for Tier 1 interventions. Previous research has demonstrated the importance of preventative interventions (Olson, 2013), in part, due to the adverse effects of relatively few days missed (Ingul et al., 2012; Skedgell &

Kearney, 2016). Hypothesis two is that 3% of full school days missed (e.g., 5.4 school days) will be the best cutoff for Tier 2 interventions. There is a lack of research on the 3% cutoff as only one study utilized this cutoff (Fornander, 2018). Hypothesis three is that 10% of full school days missed (e.g., 18 school days) will be the best cutoff for Tier 3 interventions. Previous research has identified the 10% cutoff as an appropriate definition for Tier 3 (Balfanz & Byrnes, 2012; National Center for Education Statistics, 2016).

Study two aimed to address these problems by identifying the most relevant family environment risk factors among youth with problematic school absenteeism and categorizing students into the MTSS tiers based on their level of severity. Hypothesis four is that level of organization will be the most relevant family environment risk factor for youth at the highest risk of displaying problematic school absenteeism. Research addressing the association between family environment and problematic school absenteeism is lacking. Of the available research, families defined as structure-oriented or with increased level of organization were associated with an increased risk of youth eating disorders and trichotillomania and are overrepresented in mental health clinics and the juvenile justice system (Felker & Stivers, 1994; Keuthen, Fama, Altenburger, Allen, & Pauls, 2013; Moos & Moos, 1976; Scoresby & Christensen, 1976).

Study three aimed to address this problem by identifying the most relevant youth psychopathology risk factors among youth with problematic school absenteeism and categorizing students into the MTSS tiers based on their level of severity. Hypothesis five is that major depression will be the most relevant internalizing symptom for youth at the highest risk of displaying problematic school absenteeism, and separation anxiety symptoms will be the second most relevant internalizing symptom. Previous research has found youth with problematic school absenteeism display symptoms of major depression (Ek & Eriksson, 2013; Haight et al., 2011;

Wood et al., 2012) and separation anxiety (Hughes, Gullone, Dudley, & Tonge, 2010; Maynard et al., 2015).

CHAPTER 2

STUDY 1

Reconciling Contemporary Approaches to School Attendance and School Absenteeism: Toward Promotion and Nimble Response, Global Policy Review and Implementation, and Future Adaptability (Part 1)

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Keywords: School attendance[1], school absenteeism[2], chronic absenteeism[3], truancy[4], school refusal[5], school withdrawal[6], school exclusion[7], multi-tiered system of supports[8], multidimensional multi-tiered system of supports pyramid model[9], early warning[10], dissemination and implementation[11], future adaptability[12].

Abstract

School attendance is an important foundational competency for children and adolescents, and school absenteeism has been linked to myriad short- and long-term negative consequences, even into adulthood. Many efforts have been made to conceptualize and address this population across various categories and dimensions of functioning and across multiple disciplines, resulting in both a rich literature base and a splintered view regarding this population. This article (Part 1 of 2) reviews and critiques key categorical and dimensional approaches to conceptualizing school attendance and school absenteeism, with an eye toward reconciling these approaches (Part 2 of 2) to develop a roadmap for preventative and intervention strategies, early warning systems and nimble response, global policy review, dissemination and implementation, and adaptations to

future changes in education and technology. This article sets the stage for a discussion of a multidimensional, multi-tiered system of supports pyramid model as a heuristic framework for conceptualizing the manifold aspects of school attendance and school absenteeism.

Introduction

School attendance and successful graduation from high school or its equivalent have long been recognized as crucial foundational competencies for children and adolescents. Strong school attendance and successful graduation are closely linked to broad, positive outcome variables such as enhanced lifetime earning potential and economic empowerment (Balfanz, 2016; Balfanz et al., 2014), opportunities for higher education and other avenues of adult and career readiness (Darling-Hammond, Wilhoit, & Pittenger, 2014), improved health and reduced death rates (Allison & Attisha, 2019; Freudenberg & Ruglis, 2007), better civic engagement and outcomes (DePaoli, Balfanz, Atwell, & Bridgeland, 2018; Zaff et al., 2017), and critical thinking, risk aversion, and life skills that impact positive economic and health-based choices (Brunello & De Paola, 2014). In related fashion, strong school attendance and successful graduation may enhance quality of life and buffer against negative mental and physical health outcomes (Lee et al., 2016; Rumberger, 2011; US Census Bureau, 2012).

Conversely, school attendance problems, including school absenteeism, have long been recognized as a critical developmental challenge and limiting factor for children and adolescents (Kearney, 2016). School attendance problems in various forms have been linked to a wide array of academic deficiencies such as reduced educational performance, lower reading and mathematics test scores, fewer literacy skills, grade retention, and school dropout (Bridgeland, Dilulio, & Morison, 2006; Burton, Marshal, & Chisolm, 2014; Smerillo, Reynolds, Temple, & Ou, 2018). School attendance problems are closely linked as well to internalizing behavior problems such as anxiety, depression (including issues of suicidal behavior and bereavement), and social isolation (Ek & Eriksson, 2013; Finning et al., 2019; Knollman, Reissner, & Hebebrand, 2019; Miller, Esposito-Smythers, & Leichtweis, 2015; Pompili et al., 2013) as well as externalizing behavior problems such as elevated alcohol, tobacco, marijuana, and other drug use (Henry & Huizinga, 2007; Holtes et al., 2015), risky sexual behaviors (Allison & Attisha, 2019), oppositional defiant and conduct problems (Wood et al., 2012), impaired social functioning and poor relationships with peers (Gonzálvez et al., 2019; Havik, Bru, & Ertesvag, 2015), and involvement with the juvenile justice system (Anderson et al., 2016). School attendance problems are connected to myriad adverse childhood experiences such as trauma, school violence and victimization, and medical problems as well (Berendes, Andujar, Barrios, & Hill, 2019; Emerson et al., 2016; Hsu, Qin, Beavers, & Mirabelli, 2016; Hutzell & Payne, 2012; McLean, Peterson, King, Meece, & Belongia, 2017; Ramirez et al., 2012; Stempel, Cox-Martin, Bronsert, Dickinson, & Allison, 2017).

School attendance problems have long-lasting effects even into adulthood, including enhanced risk for marital and psychiatric problems (Hibbett & Fogelman, 1990), non-violent crime and substance use (Henry, Knight, & Thornberry, 2012; Rocque, Jennings, Piquero, Ozkan, & Farrington, 2017), and occupational problems and economic deprivation (Bridgeland et al., 2006; Christenson & Thurlow, 2004). Students who drop out of high school are 24 times more likely than graduates to experience 4 or more negative life outcomes (Lansford, Dodge, Pettit, & Bates, 2016). The societal outlays for school dropout are substantial as well, including elevated economic costs due to increased crime, incarceration, public assistance, unemployment, and medical coverage as well as reduced mobility, tax revenues, earnings, entrepreneurship, and productivity (Latif, Choudhary, & Hammayun, 2015; Levin, 2017; Marchbanks et al., 2014).

School attendance problems have no consensus definition (see later section) but lack of school attendance as well as permanent school dropout have been identified as widespread global phenomena with substantial prevalence rates, especially among developing areas such as sub-Saharan and northern Africa and southern and western Asia. Nearly one of five children and adolescents worldwide (17.8%) are out of school, a rate more than doubled among upper secondary school-age youth (36.3%) and elevated among girls and those in low-income countries. Even in Europe and North America, the out-of-school rate is 4.3% (UNESCO, 2018). In the United States, the high school graduation rate is 84.1%, the status dropout rate is 6.1%, and the chronic absenteeism rate (federally defined as missing 15+ (8.3%) days of school in one academic year) is 16.0%, a rate elevated among diverse youth, students with disabilities, and high school students (21.1%) (DePaoli et al., 2018; National Center for Education Statistics, 2018; US Department of Education, 2019). As such, school attendance is often viewed as a key linchpin for prevention science and for curbing mental health and other problems in children and adolescents worldwide (Catalano et al., 2012; Kieling et al., 2011).

The substantial impact and prevalence of school attendance and school absenteeism (SA/A) has led researchers across many disciplines to study these phenomena, including those in psychology, education, criminal and juvenile justice, social work, medicine, psychiatry, nursing, epidemiology, public and educational policy, program evaluation, leadership, child development, and sociology, among other professions (Birioukov, 2016; Elliot, 1999; Kearney, 2003). Research in this area has been conducted for over a century, making SA/A among the longest-investigated issues among children and adolescents (Kearney, 2001). This lengthy period of study has led to a plethora of terms and approaches to describe this population, which has led simultaneously to a rich literature base but also to considerable splintering across disciplines and thus a lack of consensus with respect to defining, conceptualizing, classifying, assessing, and addressing SA/A (Kearney, 2016, 2019). Such splintering has likely led to dissemination and implementation barriers regarding empirically-based strategies for SA/A (Arora et al., 2016).

Evolution of Concepts in SA/A

The purpose of this article is to draw upon this rich and disparate literature base to begin to reconcile various contemporary approaches to SA/A and to develop a heuristic framework for conceptualizing this population moving forward. Such a framework is necessary given several needs: to promote school attendance as much as to reduce absenteeism, to respond nimbly to emerging school attendance problems, to inform policy review, to provide general applicability to various jurisdictions and cultures, and to adapt to future and rapid changes in education and technology. As such, a contemporary framework for SA/A will need to be inclusive, flexible, applicable, educational, and pliable.

Efforts to conceptualize SA/A are manifold, in part because of the heterogeneous nature of the constructs and because risk factors for these problems are multilayered and myriad (van der Woude, van der Stouwe, & Stams, 2017). However, these conceptualization efforts can be grouped generally into categorical and dimensional approaches. Historical efforts to conceptualize SA/A began with categorical terms, dichotomies, and distinctions to try to sort youth with school attendance problems into defined groups in an effort to better understand the mechanisms underlying such behaviors (Kearney, 2001). Categorical approaches broadly aim for within-category homogeneity and between-category qualitative differences (De Boeck, Wilson, & Acton, 2005), goals that have been somewhat elusive for SA/A (DiBartolo & Braun, 2017).

Other efforts to conceptualize SA/A have focused more on dimensional approaches to better reflect the heterogeneity, fluidity, scalability, and complexity of these constructs (Kearney & Silverman, 1996). Such approaches, described in more detail in later sections, focus on fluid or latent constructs such as attendance profiles, absenteeism severity, risk factors, functions, and interventions that can be arranged along various spectra or continua (Maynard, Salas-Wright, Vaughn, & Peters, 2012). Dimensional approaches generally aim for within-category heterogeneity and between-category quantitative differences (De Boeck, Wilson, & Acton, 2005), goals that can also be challenging for SA/A (Heyne, Gren-Landell, Melvin, & Gentle-Genitty, 2019).

The juxtaposition of categorical and dimensional approaches to mental health and related challenges has led historically to strong debates about which approach best characterizes a given phenomenon or set of phenomena such as mental disorders (Widiger & Samuel, 2005). Such debate is intensified by the fact that specific taxa for personality and psychopathology are difficult to distinguish even though clinicians and educational and mental health agencies often rely on categorical approaches (Haslam, Holland, & Kuppens, 2012). In addition, mental disorders and psychopathological constructs can be categorically different from normal function in some cases (e.g., psychotic or eating disorder) but not in other cases (e.g., personality disorder, worry), further muddying the classification waters (Ruscio & Ruscio, 2008).

Coghill and Sonuga-Barke (2012) described several avenues for reconciling this debate with respect to mental health and other challenges in children and adolescents. These avenues include replacing categorical with dimensional approaches at various levels or utilizing a mixed approach whereby categories and dimensions are considered alongside one another. With respect to the latter avenue, this could include allowing some phenomena to be described categorically (e.g., autism, endogenous depression) and other phenomena to be described dimensionally (e.g., psychopathy, exogenous depression). Or, in a mixed approach, both categorical and dimensional approaches could be used together within the same class of disorder (e.g., the category of attention-deficit/hyperactivity disorder with dimensions of inattentiveness and hyperactivity/impulsivity). Coghill and Sonuga-Barke (2012) maintained that systems based on both categorical and dimensional approaches can coexist within a single problem by serving different but equally useful purposes.

The next sections of this article (Part 1 of the review) contain brief descriptions of common categorical terms and distinctions as well as dimensional approaches to the study of SA/A. These sections also briefly describe the advantages and disadvantages of each method. In Part 2 of this review, we adopt Coghill and Sonuga-Barke's (2012) premise that both categorical and dimensional approaches can be applied to a given heterogeneous construct such as SA/A and, indeed, that these approaches are wholly compatible with one another with respect to SA/A. In addition, such compatibilities may be helpful for developing a roadmap for researchers, clinicians, and educators to follow as they work to develop preventiative and nimble responses to SA/A, disseminate research work, and adapt to future changes in education and technology.

Terminology

As mentioned, school attendance problems have no consensus definition, in part because of the various terms used to describe this population from different disciplines. This section provides general descriptions of common categorical terms utilized in the field, with the strong caveat that considerable controversy and heterogeneity remain even with respect to these characterizations (Kiani, Otero, Taufique, & Ivanov, 2018). Most broadly, *school attendance* has traditionally referred to a student's complete in-class physical presence during an academic day and *school absenteeism* has traditionally referred to a student's complete in-class physical absence during an academic day (Kearney, 2019). School absenteeism is sometimes categorized as *excused* or *unexcused* (or *authorized* or *unauthorized*) in nature, referring to absence due to some legitimate reason such as illness or absence due to some illegitimate reason such as peer association outside of school (Gottfried, 2009). *School attendance problems*, which can include school absenteeism, refer generally to either a collection of different kinds of absences (e.g., late to school/tardiness; skipped class or missed time of day) or to general difficulties attending or getting to school that can involve a wide array of individual and contextual factors (Kearney, 2016). School attendance problems can lead eventually to *school stopout*, which refers to temporary departure from school prior to graduation, and/or s*chool dropout/stayout*, which refers to permanent, premature departure from school prior to graduation (Boylan & Renzulli, 2017).

Several terms in the literature refer generally, though not always, to youth-based school attendance problems, or absences initiated primarily by a child or adolescent, with the caveat that many different risk factor levels (e.g., parent, peer, school) apply to this population. *Truancy* is one of the oldest terms for school attendance problems and refers generally to illegal, unexcused (see later section) school absenteeism. Truancy is a term often utilized by school districts and/or larger entities to construct policies and definitions, such as 10 unexcused absences in a given semester or 15-week period, that trigger some legal, punitive, or administrative consequence (Sutphen, Ford, & Flaherty, 2010). From a research perspective, truancy is often associated as well with delinquency, externalizing behavior problems, and social conditions such as poverty (Zhang et al., 2010).

School refusal refers broadly to school attendance problems due to emotional difficulties such as general and social and separation anxiety, worry, distress, and sadness (Elliot & Place, 2019). A related but archaic term, *school phobia*, refers more specifically to fear-based school attendance problems such as avoidance of a specific object at school or related to school (e.g., alarm, animal, bus) that leads to absenteeism (Inglés, Gonzalvez-Macia, Garcia-Fernandez, Vicent, & Martínez-Monteagudo, 2015). *School refusal behavior* refers to a child-motivated refusal to attend school or difficulties remaining in classes for an entire day (Kearney & Silverman, 1990, 1996). School refusal behavior may or may not be related to emotional distress about school, and thus serves as an umbrella term for constructs such as truancy and school refusal.

Other terms in the literature refer to school attendance problems initiated primarily by entities other than the child, again with the caveat that multiple risk factor levels apply to each. *School withdrawal* refers generally to parent-initiated school absenteeism (Kahn & Nursten, 1962; Kearney, & Fornander, 2018). Parents or other caregivers may deliberately keep a child home from school for employment or child care purposes, to conceal maltreatment, to protect a child from perceived harm (e.g., school violence or victimization, kidnapping by an ex-spouse), to punish a child, or to mitigate a parent's separation anxiety or psychopathology due to anxiety, depression, substance use, or other problem, among other reasons (Kearney, 2001).

In addition, *school exclusion* refers generally to school-initiated absenteeism. Such exclusion may involve lawful exclusionary disciplinary practices such as suspension or expulsion for behavior problems or for, ironically, school absenteeism (Maag, 2012). School exclusion practices are often associated with zero tolerance policies regarding certain student behaviors, particularly those related to violence and other dangerous behavior (Theriot, Craun, & Dupper, 2010). School exclusion may also involve unlawful, unclear, or more nefarious reasons such as sending students (in particular special needs students) home or restricting their ability to attend school without official documentation (McCluskey, Riddell, Weedon, & Fordyce, 2016).

Categorical Distinctions

Related to these historical terms have been various broad-band and etiologically-based categorical dichotomies and distinctions for SA/A. These dichotomies and distinctions have been generally designed to carve out groups of youth with different school attendance problems to help identify causal factors as well as basic treatment direction and scope (Reid, 2013).

School refusal-truancy

An enduring categorical dichotomy has involved school refusal-truancy, which has been historically based on an internalizing-externalizing behavior problem distinction (Young, Brasic, Kisnadwala, & Leven, 1990). School refusal is often linked to internalizing difficulties such as anxiety and depression, whereas truancy is often linked to externalizing difficulties such as oppositional and conduct problems (Dembo, Wareham, Schmeidler, & Winters, 2016). In addition, school refusal is sometimes associated with parental knowledge of a child's absenteeism, whereas truancy is often tied to lack of parental knowledge (Bobakova, Geckova, Klein, van Dijk, & Reijneveld, 2015). School refusal may be more associated with primary or early secondary grades, whereas truancy may be more associated with later secondary grades (Melvin et al., 2017; Pengpid & Peltzer, 2017). School refusal may be more associated with certain family dynamics such as enmeshment, whereas truancy may be more associated with certain family dynamics such as conflict (McConnell & Kubina, 2014; Richardson, 2016).

A main advantage of a school refusal-truancy distinction is its face validity, as some children are clearly anxious and thus avoidant of school whereas some adolescents refuse or decline to attend school without emotional difficulty and with perhaps more delinquency (Berg, 1997; Evans, 2000). The dichotomy carries a significant number of disadvantages, however. First, numerous studies and reviews have demonstrated considerable heterogeneity *within* each construct (Inglés, Gonzalvez-Macia, Garcia-Fernandez, Vicent, & Martínez-Monteagudo, 2015). School refusal is linked to a wide variety of anxiety- and mood-based conditions in addition to fairly broad terms such as emotional distress, avoidance, malingering, dread, worry, fear, somatic complaints, and negative affectivity (e.g., Sibeoni et al., 2018). In addition, truancy is a highly heterogeneous construct with multiple dimensions related to academic status, disability profile, location, race/ethnicity, activities in and out of school, individual-group-orientation, premediated-spontaneous, parental academic involvement, and type and number of classes skipped, among many other variables (Chen, Culhane, Metraux, Park, & Venable, 2016; Dahl, 2016; Keppens & Spruyt, 2017; Maynard et al., 2017; Reid, 1999; Salzer & Heine, 2016). Truancy as a legal construct is also highly variably defined across many jurisdictions (Gentle-Genitty et al. 2015).

Second, many researchers have demonstrated substantial heterogeneity *across* the two constructs. Both school refusal and truancy have been associated, for example, with learning and health difficulties, effects from bullying, social interaction problems, maltreatment, chronic illness, and, of course, missing school (Katz, Leith, & Paliokosta, 2016; Lum et al., 2017). In addition, both constructs can be similarly influenced by broader classes of contextual factors related to peers, schools, and communities (Baier, 2016; Burdick-Will, Stein, & Grigg, 2019; Sugrue, Zuel, & LaLiberte, 2016). Many historical and statistical studies have also demonstrated either considerable overlap of school refusal and truancy and/or other, large unclassified categories (Atkinson, Quarrington, Cyr, & Atkinson, 1989; Berg et al., 1985; Bools, Foster, Brown, & Berg, 1990; Cooper, 1986; Dube & Orpinas, 2009; Torma & Halsti, 1975). Many researchers historically have gravitated toward conclusions of dimensionality to describe this population (e.g., Hersov, 1985; Kolvin et al., 1984; Rubenstein & Hastings, 1980).

More specifically, meta-analytic and large-scale studies reveal broad, extensive overlap of internalizing and externalizing symptoms, absence types, and interventions for school refusal and truancy (Egger, Costello, & Angold, 2003; Finning et al., 2018, 2019; Maynard et al., 2012, 2018). Neither pathognomonic nor reliable assident factors associated with the constructs have been identified, which often leads to interchangeable use of the terms in research and clinical practice (Brandibas, Jeunier, Clanet, & Fourasté, 2004). Contemporary notions of school refusal and truancy address these concerns to a degree (Heyne, Gren-Landell et al., 2019), though commonalities remain, such as tantrums, physical symptoms, reluctance or refusal to attend school, depression, sleep problems, variability in school attendance, and parental desire to have a child back in school.

Third, in related fashion, a school-refusal truancy distinction tends to erode in value at the point of clinical presentation. In the modern technological age, many parents are informed immediately of a child's school absence, diminishing the value of distinguishing absenteeism based simply on parental knowledge or even consent (Smythe-Leistico & Page, 2018). Some parents are also skilled at securing medical notes or other methods to induce schools to record absences as excused in nature (Chang et al., 2016). In addition, many children initially miss school due to anxiety but are later drawn to the amenities of staying home, and many adolescents who have been out of school for some time experience spikes in anxiety upon initial reintegration to school. Indeed, many youth described with school refusal or truancy traverse frequently between these groups (Birioukov, 2016). Clinicians are thus often faced with the challenge of choosing the best intervention for a child's school attendance problems that appear to be of various types (Kearney & Albano, 2018; Maynard et al., 2013).

Finally, the concept of truancy carries with it many negative connotations that are not necessarily ascribed to concepts such as school refusal. Truancy is often used as a legal or institutional term, whereas school refusal is not, which may create stigmatization problems (Campbell & Wright, 2005; Strand, 2014). Indeed, anxiety-related school refusal may be viewed more sympathetically by school staff than truancy (Finning et al., 2019) and the label of truancy is often associated with willful, deliberate, deviant behavior (Birioukov, 2016; Lyon & Cotler, 2007). Educational and mental health agencies often emphasize the concept of truancy (in some form) in their definitions and discussions of problematic school absenteeism, but rarely that of school refusal or related terms (Gleich-Bope, 2014).

In related fashion, the overall concept of truancy has been criticized as representing more of a punitive paradigm that disproportionately affects vulnerable and at-risk youth and that contributes to the school-to-prison pipeline (Mallett, 2016; Nauer, 2016). The concept of truancy also tends to be associated with lower socioeconomic youth who experience barriers to attending school such as domestic and neighborhood violence, unstable housing conditions, lack of school supplies, housing and transportation problems, and safety concerns coming to school (Flaherty, Sutphen, & Ely, 2012; Gottfried, 2017). Others view truancy less as an aberrant behavior than as a form of systemic discrimination that reflects the uneven distribution of social goods and opportunities within a larger society (Yang & Ham, 2017); others see truancy as deliberate student resistance against an unfair academic system (McIntyre-Bhatty, 2008).

Excused-unexcused absences

Many school districts and some researchers also utilize an excused-unexcused absences dichotomy to categorize school attendance problems (Hough, 2019). Key advantages of this approach include its administrative practicality and simplicity, linkage to district and state policies regarding excessive absenteeism, historical connection (unexcused absences) to truancy, and utility in examining ratios of excused to unexcused absences (Gottfried, 2009). In addition, some have found that students absent without permission display approximately twice the odds of engaging in risky behaviors (e.g., unintentional injuries and violence, substance use, sexual behaviors) than students absent with permission (Eaton, Brener, & Kann, 2008). Others have found that anxiety and depression symptoms are good predictors of unexcused absences in sexual minority youth (Burton, Marshal, & Chisolm, 2014).

An excused-unexcused absence dichotomy has several disadvantages, however. Numerous studies have illustrated ancillary problems associated with school absenteeism whether excused or unexcused, combine these absences when evaluating outcomes, or have found few differences based on this absence typology (Baker & Jansen, 2000; Morrissey, Hutchison, & Winsler, 2013; Redmond & Hosp, 2008; Spencer, 2009; Wood et al., 2012). For example, Gottfried (2009) found that excused and unexcused absences were both significantly related to various demographic, academic, and behavioral variables. Dube and Orpinas (2009) similarly found no difference between excused and unexcused absences across various profiles of youth with school attendance problems. The fidelity of data collected by school districts in this regard remains problematic as well, particularly because the arbiter of whether an absence is excused or unexcused is typically a family member and sometimes not a parent (Birioukov, 2016; Conry & Richards, 2018). In addition, excused absences may include legitimate reasons such as illness but also institutional or questionable reasons such as court dates, school suspensions, family vacations, or minor health conditions accommodated by physician notes (Outhouse, 2012; Reid, 2007).

In addition, reliance on an excused-unexcused absence dichotomy, particularly within school districts, often delays intervention until some legal tripwire is triggered (e.g., 10 unexcused absences in a semester). Some have criticized this approach as a "wait to fail" process that can enhance risk for school dropout (Cramer, Gonzalez, & Pellegrini-Lafont, 2014; Kearney & Graczyk, 2014). Indeed, the importance of early intervention for school attendance problems is quite clear in the literature (McCluskey, Bynum, & Patchin, 2004; Sutphen et al., 2010). From a clinical perspective, evaluating total amount of time missed from school for any reason for a particular case may be advisable (Kearney & Albano, 2018).

School withdrawal and school exclusion

As mentioned earlier, other categorical distinctions for school absenteeism have focused on parent-initiated (school withdrawal) and school-initiated (school exclusion) reasons. Potential explanations for parent-initiated school withdrawal were noted earlier. School exclusion can refer to disciplinary practices administered for absenteeism and other behavioral infractions, which usually means a child is not allowed to attend classes for a set period of time (Parker et al., 2015). Suspension can be in-school, meaning a child is physically in the school building but not in class, or out-of-school, meaning a child is not allowed on the school campus until certain requirements (e.g., parent conference, time away) are met. In related fashion, expulsion refers to permanent, administrative separation from a particular school, which sometimes applies to very severe infractions and possibly absenteeism and sometimes in response to zero tolerance policies (Allman & Slate, 2011). Other exclusionary practices such as detention may be utilized as well.

In addition, as noted earlier, others have focused on school exclusion as school-initiated absence that is unlawful or that represents lack of appropriate accommodations (Reid, 2010).

A key advantage of identifying school withdrawal and school exclusion in cases of absenteeism involves rapid identification of non-child-based reasons for nonattendance and thus alternative assignment of treatment resources (e.g., toward parents or working with school officials) (e.g., Daniels & Cole, 2010). However, school district policies that emphasize suspension and expulsion to address school attendance problems lead paradoxically to more dropout, delinquency, lag in academic achievement, and student involvement with the juvenile justice system (Monahan, VanDerhei, Bechtold, & Cauffman, 2014; Stone & Stone, 2011; Suh, Suh, & Houston, 2007). In addition, school exclusion does not appear to differ among various clusters of youth with school absenteeism (Gallé-Tessonneau, Johnsen, & Keppens, 2019). Unlawful school exclusion is also vaguely defined, difficult to track, and easily reframed as lawful school exclusion (McCluskey et al., 2016).

School exclusion policies also tend to be disproportionately assigned to low-income and diverse students (Shabazian, 2015). As such, exclusionary disciplinary policies have come under harsh criticism and are increasingly being reviewed and de-emphasized in many districts (Curran, 2016; Perry & Morris, 2014). Alternative responses that include greater proximity to school could involve sanctions such as in-school suspension and school-based community service as well as restorative practices such as mentoring and remediation of academic difficulties (Gregory, Huang, Anyon, Greer, & Downing, 2018; Haight, Chapman, Hendron, Loftis, & Kearney, 2014; McNeill, Friedman, & Chavez, 2016).

Acute-chronic

Another common historical dichotomy has been to distinguish acute from chronic school absenteeism. Though variously defined, acute cases of absenteeism often refer to those lasting less than one calendar year, whereas chronic cases of absenteeism often refer to those lasting more than one calendar year, or at least across two or more academic years (Baker & Wills, 1978; Berg et al., 1985). Some also distinguish between self-corrective problems lasting less than two weeks and acute problems lasting 2-52 weeks (Kearney & Silverman, 1996; Mauro & Machell, 2019). An acute-chronic distinction has been linked as well to more immediate onset involving emotional distress, akin to school refusal, and more insidious onset involving conduct problems, akin to truancy (Pellegrini, 2007). As such, an acute-chronic distinction is sometimes associated with other historical dichotomies such as Type 1-Type 2, common-induced, and neurotic-characterological (Kearney, 2001).

A key advantage of an acute-chronic distinction is a quick delineation of length of an absenteeism problem, which can be generally associated with breadth of intervention needed to resolve the problem. In general, more lengthy cases of absenteeism require more complex intervention and with multiple parties than less lengthy cases (Thambirajah, Grandison, & De-Hayes, 2008). Prognostic outcomes for youth with more lengthy absenteeism tend to be poorer than those with less lengthy absenteeism (Kearney, Turner, & Gauger, 2010). An understanding of a child's developmental history regarding his or her school attendance problems has substantial clinical value as well (Veenstra, Lindenberg, Tinga, & Ormel, 2010). Disadvantages to an acute-chronic distinction include variable timelines posed by researchers and the need for more empirical data to support a particular timeline distinction (Balfanz & Byrnes, 2012; Kearney, 2003).

Diagnostic categories

Other categorical distinctions with respect to school absenteeism have involved attempts at diagnostic groupings. Such groupings often involve anxiety, mood, and disruptive behavior disorders, including some combination of these (Bernstein & Garfinkel, 1986; Kearney & Albano, 2004; Last & Strauss, 1990; McShane, Walter, & Rey, 2001). Anxiety- and mood-based categories are sometimes clustered in some youth with school attendance problems, as are oppositional defiant and conduct problems (King, Heyne, Tonge, Gullone, & Ollendick, 2001). As such, these distinctions are sometimes applied or related to school refusal-truancy or acute-chronic distinctions (Ek & Eriksson, 2013). Prognosis may relate to a degree to specific diagnostic type in this population as well (Layne, Bernstein, Egan, & Kushner, 2003; McShane, Walter, & Rey, 2004).

Diagnostic groupings are appealing to many researchers and clinicians, but considerable diagnostic heterogeneity is a hallmark of youth with school attendance problems (Kearney, 2007; Nayak, Sangoi, & Nachane, 2018). In addition, several studies indicate that many youth with school attendance problems have no psychiatric diagnosis at all (Egger et al., 2003; Kearney & Albano, 2004). School attendance problems are not formally listed as psychiatric disorders in most nomenclatures, though aspects of these problems are represented in separation anxiety disorder and conduct disorder (American Psychiatric Association, 2013). As such, diagnostic profiles in this population have not been linked extensively to intervention recommendations.

Summary

Categorical and dichotomous approaches to school attendance problems have a rich scholarly history and have contributed substantially to the conceptualization of this population. In addition, such approaches are well inculcated into many legal statutes, school-based policies, and research frameworks regarding school absenteeism. Key challenges for categorical and dichotomous approaches to school attendance problems include the need to better account for the considerable heterogeneity of this population and to link specific intervention strategies to specific constructs. In addition, these traditional characterizations are becoming challenged in an era of virtual learning, distance-based classrooms, hybrid education, blended education (e.g., high school with community college or vocational training), and other forms of alternative approaches toward graduation or career/adult readiness (see also Part 2 of this review). Categorical and dichotomous approaches to school attendance problems also do not generally focus on promoting school attendance, instead adopting more of a tertiary approach.

Dimensional Approaches

As mentioned earlier, researchers and others have also examined dimensional approaches to SA/A to try to better account for the fluidity, scalability, and complexity of these constructs. These dimensional approaches include a focus on conceptualizing various aspects of SA/A along continua or spectra to more fully capture the heterogeneity, variability, diversity, and mutability of this population. General dimensions to be discussed over the next sections include definition, tiers of prevention/intervention, risk and contextual factors, absenteeism severity, developmental and school levels, and functional profiles.

School attendance and its problems on a definitional continuum

One of the most fundamental dimensional approaches to SA/A involves definition itself. This approach involves viewing school attendance and its various associated problems along a spectrum of panels ranging from full presence to complete absence (Figure 13). School attendance, with or without challenges or problems, generally represents the left side of the spectrum and can include attendance with little to no difficulty, early warning signs that may signal later absenteeism, school attendance under considerable distress, and morning misbehaviors designed to induce parental acquiescence or other responses that may eventually lead to absence from school (Kearney, 2019). Common early warning signs that may signal later absenteeism include frequent requests to leave the classroom or to contact parents, difficulties attending specialized sections of a school building (e.g., gymnasium, cafeteria), difficulties transitioning from class to class, persistent distress, and sudden changes in grades, completed work, or behavior, among others (Kearney & Graczyk, 2014).

The middle of the spectrum generally represents school attendance mixed with school absenteeism in some form, such as arriving late to school, missing some classes or times of day but not others, and periodic absences during a particular week, including early departures from school (Boylan & Renzulli, 2017). The right side of the spectrum represents complete school absenteeism, typically for an extended period of time in the form of school stayout (including school disengagement) or permanently in the form of school dropout (Iachini, Petiwala, & DeHart, 2016). The latter features of the spectrum account as well for the observation from many researchers that leaving school permanently is more of a process than an event (e.g., Ananga, 2011; Dupéré et al., 2015; Wang & Fredricks, 2014).

A key advantage of a dimensional approach to defining SA/A is that it includes the construct of school attendance and captures the full range of possible school attendance problems along a spectrum (Tobias, 2019). The spectrum allows for peri-attendance phenomena that are often fluid and change for a particular child over a certain time period (Chu, Guarino, Mele, O'Connell, & Coto, 2019; Kearney, 2019; Knollmann, Reissner, & Hebebrand, 2019). For example, Pflug and Schneider (2016) found, among students with absenteeism in the past 7 days, that 35.0% missed a single class or part of a school day, 31.3% missed an entire day, and 33.7%

missed 2+ days. In addition, the spectrum can account for the developmental history often surrounding SA/A in particular student, which can deteriorate over time in stages from full attendance to full absence (Henry, Knight, & Thornberry, 2012). The spectrum is also largely atheoretical and may apply to various pathways to school dropout across countries (Lamb, Markussen, Teese, Sandberg, & Polesel, 2011).

Such a dimension or spectrum allows for nimble, rapid, and real-time assessment of type of school attendance problem, which must be a priority for implementation models (see Part 2 of this review; Green et al., 2015). The dimension can also apply to variability in absenteeism that can exist between children in a given classroom, between classrooms in the same school, and between schools (Gee, 2019). The dimension also avoids pitfalls often associated with excused and unexcused absences by focusing more on type of school attendance problems and less on the need to establish the validity of an absence (Kearney & Albano, 2018). The dimension can apply as well to various tiers of SA/A (see next section).

Key drawbacks of the definitional spectrum include its lack of current utility in school districts and research studies, inability to provide information about the etiology or function of a school attendance problem, and lack of association with prevention or intervention protocols for this population (Balfanz, & Byrnes, 2018; Schildkamp, Poortman, & Handelzalts, 2016). Specific, operational definitions for each panel of the spectrum remain needed as well (Kearney, 2016). Others contend that collecting even very basic absenteeism data is challenging enough for many schools, and that basic data may be sufficient for at least determining which students are missing a substantial amount of school (Birioukov, 2016). Still, researchers commonly examine school attendance problems other than full absenteeism, clinicians and others must initially grapple with the exterior complexity of this population, and the spectrum can be a useful heuristic for understanding the full scope of school attendance and its problems across jurisdictions (Kearney, 2019; Keppens & Spruyt, 2017; Wegmann, & Smith, 2019).

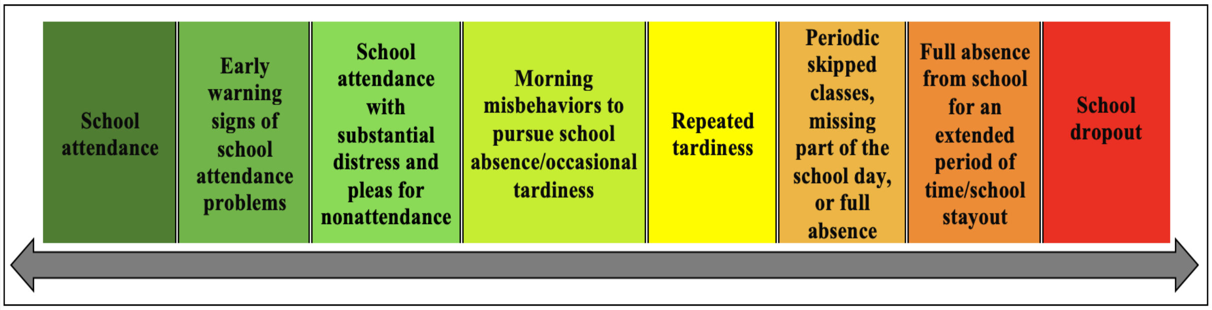

Figure 13. Spectrum of school attendance and its problems

Multi-tiered system of supports

As noted earlier, the sheer number of disciplines associated with the study of SA/A has led to a plethora of intervention approaches to address this complicated population. Such approaches range from (1) systemic prevention strategies developed by educators and criminal justice experts to promote school attendance and curb dropout, (2) clinical approaches developed by health professionals to address mental health and other challenges during emerging school absenteeism, (including aspects described in the previous section) and (3) intensive strategies developed by professionals in multiple disciplines to address chronic and severe absenteeism and potential dropout often mixed with substantial, broad contextual factors related to extreme psychopathology, family crises, and school and community variables (Freeman & Simonsen, 2015; Wilson, Tanner-Smith, Lipsey, Steinka-Fry, & Morrison, 2011). An advantage of these varied set of approaches is as much a focus on promoting school attendance and preventing school attendance problems as on ameliorating existing cases of school absenteeism (Ekstrand, 2015).

Kearney and Graczyk (2014; see also Kearney, 2016) advocated the use of multi-tiered system of support principles to arrange extant strategies to boost school attendance and to address school absenteeism at different severity and risk/contextual factor levels. Multi-tiered system of support (MTSS) models have been utilized in education for many years and typically weave the academic focus of Response to Intervention (RtI) models and the behavioral and social focus of positive behavior intervention supports (PBIS) or program-wide positive behavior supports (PWPBS) into one cohesive model to best address all student needs (Sugai & Horner, 2009). An overarching principle of MTSS is to eschew a "wait to fail" mentality and to instead emphasize active monitoring and more immediate intervention (McIntosh & Goodman, 2016). MTSS models thus accentuate prevention, frequent progress monitoring, data-based decision-making and problem-solving, evidence-based interventions, individualized instruction and intervention, and implementation fidelity (Eagle, Dowd-Eagle, Snyder, & Holtzman, 2015). The comprehensive, empirical, sustainable, and efficient nature of MTSS is designed to optimize limited resources and is thus becoming widely adopted in school settings (August, Piehler, & Miller, 2018; McIntosh, Bohanon, & Goodman, 2010).

MTSS models commonly arrange prevention and intervention strategies for a particular problem (or non-problem) into three tiers: primary or universal (Tier 1), secondary or targeted (Tier 2), and tertiary or intensive (Tier 3) (Stephan, Sugai, Lever, & Connors, 2015; Stoiber & Gettinger, 2016). Tier 1 strategies involve delivering support to all students and are generally designed to promote a positive school culture and prosocial behavior and academic competence and to prevent difficulties in these areas. Tier 2 strategies involve delivering support to a percentage of students who do not respond in some way to Tier 1 strategies but who have less complex concerns. Tier 3 and more individualized strategies involve delivering support to a lesser percentage of students who do not respond in some way to Tier 2 strategies and who have more complex concerns (Rodriguez, Loman, & Borgmeier, 2016). The tiers represent a continuum of evidence-based practices implemented by various teams (Cook, Lyon, Kubergovic, Wright, & Zhang, 2015; Weist et al., 2018).

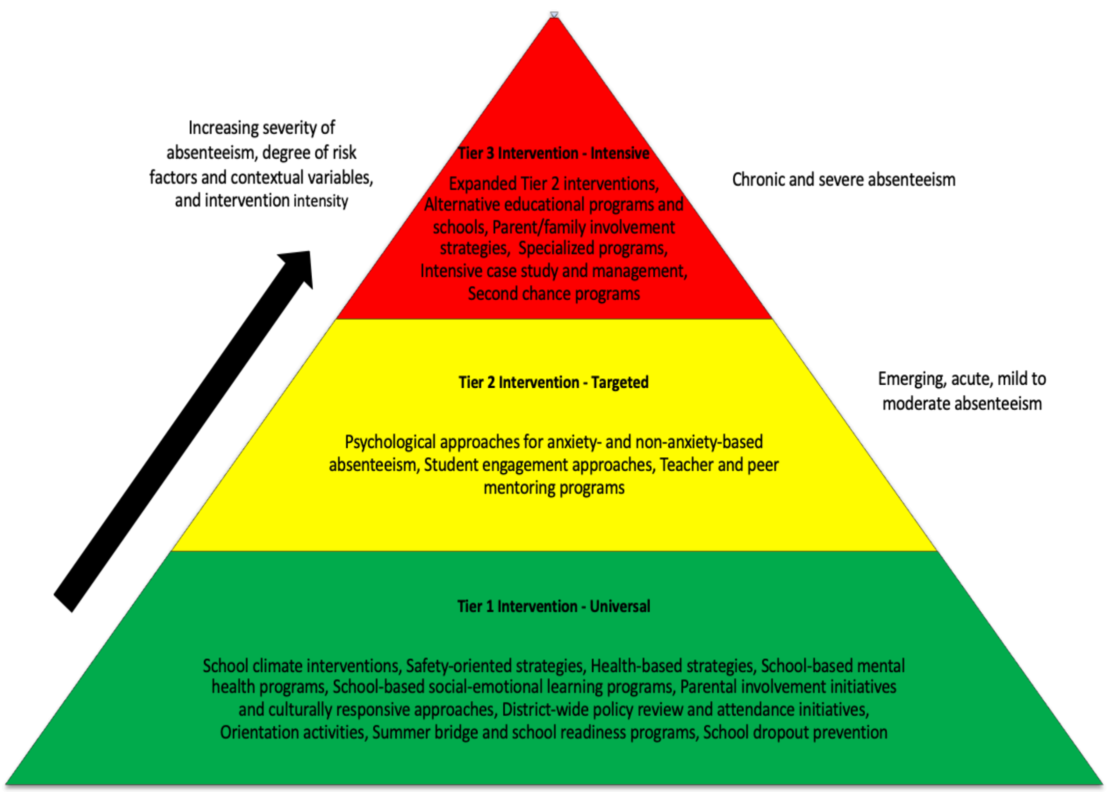

Figure 14. A multi-tiered system of supports model for SA/A.

Kearney and Graczyk (2014) initially focused on RtI descriptives for arranging strategies that promote school attendance and address school absenteeism, and Kearney (2016) later expanded this line of thinking to broader MTSS descriptives. The essential aspects of each are similar for this population: Tier 1 approaches focus on enhancing functioning and schoolwide attendance and on preventing absenteeism for all students, Tier 2 approaches focus on addressing students with emerging, acute, or mild to moderate school absenteeism, and Tier 3 approaches focus on addressing students with chronic and severe school absenteeism (Kearney, 2016; 2019; Fornander & Kearney, 2019a). Tiers 2 and 3 would thus include the definitional spectrum discussed in the previous section. Specific preventative-based and clinical and systemic interventions are matched to each tier to help school personnel and others conceptualize approaches to SA/A. Figure 14 illustrates a sample MTSS model for SA/A prevention/intervention.

An MTSS model for SA/A includes several dimensions designed to enhance inclusivity, flexibility, and adaptability to various disciplines, educational and health structures, and jurisdictions and possibly cultures. These dimensions include severity of absenteeism (e.g., percentage days missed in a given year, length of problem; see previous section), degree of risk or contextual factors present in a particular case (i.e., child, parent, family, peer, school, community), target of prevention/intervention (i.e., all students, some percentage of students, fewer percentage of students), and intensity and breadth level of interventions (e.g., less intense/broad for acute or mild to moderate absenteeism, more intense/broad for chronic and severe absenteeism). At the same time, however, an MTSS model for SA/A is designed to be fairly simple in scope to be more easily adapted to various individual cases and settings. The model is thus, essentially, a signpost or roadmap to chart available intervention strategies for SA/A.

A full description of preventative and intervention approaches to SA/A is beyond the scope of this article. In general, however, Tier 1 approaches for SA/A can include system-, district-, school-, or even community-wide or state/national approaches to promote school attendance and prevent school absenteeism, often in tandem (e.g., full service community schools; Coffey et al., 2018). These approaches are generally aimed at all students and may include methods to improve school climate and safety, to enhance mental and physical health and social-emotional functioning, to boost parent and family involvement, to reduce school violence and bullying, to review policies that may exacerbate attendance problems, and to implement orientation and readiness programs, among others (see comprehensive summaries by Kearney, 2016; Maynard, Heyne, Brendel, Bulanda, Thompson, & Pigott, 2018; Maynard, McCrea, Pigott, & Kelly, 2013; Sutphen, Ford, & Flaherty, 2010). Similarly, school dropout prevention efforts typically focus on schoolwide academic enhancement, mentoring and supportive relationships, psychosocial skill development, and effective classroom behavior management (Ecker-Lyster & Niileksela, 2016). Many of these Tier 1 approaches have been shown to improve school attendance rates, and reduce school dropout rates, either directly or indirectly (e.g., Freeman et al., 2016; Havik et al., 2015; Taylor, Oberle, Durlak, & Weissberg, 2017).

Tier 2 approaches for SA/A can include child-, parent-, and family-based interventions for cases of emerging, acute, or mild to moderate school absenteeism severity. These approaches are generally aimed at the percentage of all students/families who display these problems and may include the many psychological and psychiatric interventions designed for this population as well as approaches to enhance individual student engagement and school connectedness (Estell & Perdue, 2013; Kearney, 2019; Maynard et al., 2013, 2018). Mentoring and monitoring approaches may be relevant in this regard as well (Guryan et al., 2017; Kern, Harrison, Custer, & Mehta, 2018). Many of these Tier 2 approaches can be and have been adapted as well for more severe cases of school absenteeism (i.e., Tier 3) (Heyne et al., 2002), but many Tier 2 approaches tend to work better for cases of less severe absenteeism with fewer complicating factors (Kearney, 2016).

Tier 3 approaches for SA/A can include various system-wide school-community partnerships as well as individual approaches to address cases of chronic and severe absenteeism (Kim & Streeter, 2016). These partnerships and approaches are generally aimed at the smaller percentage of all students/families who display these problems and may include alternative educational placements and opportunities, individualized efforts to re-engage parents and family members in the educational/attendance process, and specialized programs for youth with extreme psychopathology (Flower, McDaniel, & Jolivette, 2011; Kearney, 2016; Hahn et al., 2015). A key aspect of many Tier 3 approaches to SA/A for secondary students is to focus not so much on traditional in-seat class time and formal credit accrual as much as on flexible avenues that blur the end of high school and the beginning of adult or career readiness paths such as community college, vocational training, or technical certification (Dougherty & Lombardi, 2016). As such, many approaches for this population focus more on demonstration of competencies than on traditional metrics such as grades (Castellano, Ewart Sundell, & Richardson, 2017).

An MTSS approach to SA/A remains in development and will likely need to evolve in conjunction with related progressions in the field. For example, some have advocated for moving beyond one-dimensional triangle representations of MTSS to more multifaceted pyramids, with each side of the pyramid addressing a different type of student (Dulaney, Hallam, & Wall, 2013) (see Part 2 of this review). Kearney (2016) also discussed the idea of a "Tier 4" for youth with extreme psychopathology and the need for inpatient/residential treatment mixed with education. How an MTSS approach for SA/A fits with related approaches focused on academic, behavioral, and social constructs also remains to be seen, especially given that absenteeism rates in some schools (and thus entry into Tiers 2 and 3) are overwhelming (Balfanz et al., 2014).

Still, schools that implement MTSS with higher fidelity have less school absenteeism than schools that implement with less fidelity (Freeman et al., 2016). School districts may also include attendance measures in MTSS models (Coffey et al., 2018). Others have also begun to utilize a general tiered framework to place their studies and interventions in this context (e.g., Brouwer-Borghuis, Heyne, Vogelaar, & Sauter, 2019; Elliott & Place, 2019; Ingul, Havik, & Heyne, 2019; Skedgell & Kearney, 2018). For example, Cook and colleagues (2017) evaluated a comprehensive program to reduce school attendance problems that included components of each tier of intervention. Tier 1 involved facilitating communication between teachers and parents via home visits and mobile telephone contact, Tier 2 involved attendance data monitoring and teacher intervention with students beginning to accrue excessive absences, and Tier 3 involved referrals to specialists for students with chronic absenteeism. A multidimensional MTSS framework will comprise a key piece for reconciling SA/A approaches in Part 2 of this review.

Risk/contextual factors, absenteeism severity, and developmental level

As mentioned, key dimensions of an MTSS model of SA/A involve risk and contextual factors, which are generally expected to accrue by tier in conjunction with greater absenteeism severity. Researchers commonly group risk or contextual (and, conversely, protective) factors for SA/A into various categories that include child-, parent-, family-, peer-, school-, and community-based variables (Gubbels, van der Put, & Assink, 2019; Kearney, 2008b; Zaff et al., 2017). Others have argued that broader societal or cultural variables also impact school attendance problems, including zero tolerance-based legal statutes, assimilation and language barriers, and immigration issues, among others (Casoli-Reardon, Rappaport, Kulick, & Reinfeld, 2012). Categories of risk and contextual factors for SA/A are sometimes studied singularly (e.g., Hendron & Kearney, 2016), though many recent approaches have utilized more sophisticated multilevel modeling and related statistical procedures to examine these categories collectively (Dembo et al., 2016; Ramberg, Laftman, Fransson, & Modin, 2018; Van Eck, Johnson, Bettencourt, & Johnson, 2017). An accumulation of risk/contextual factors appears to exacerbate risk of school attendance problems (Catalano et al., 2012; Ingul et al., 2012) and thus may be more evident in Tier 3 than Tier 2 cases (Vaughn, Maynard, Salas-Wright, Perron, & Abdon, 2013).

Similarly, absenteeism severity is an important dimension of an MTSS model of SA/A and can be generally measured as percentage days missed from school in a given academic year (Fornander & Kearney, 2019). However, this dimension can also be more broadly conceptualized as developmental history of a child's SA/A across multiple academic years (Veenstra et al., 2010). Risk and contextual factors as well as absenteeism severity can also change along a continuum of developmental and school levels (Skedgell & Kearney, 2018). Risk factors for school absenteeism can manifest quite differently across primary, early secondary, and later secondary grades (Suh & Suh, 2007). In addition, absenteeism severity rates in schools tend to spike in kindergarten and first grade, decline during elementary school years, spike again in middle school, and continue to increase through high school, peaking at twelfth grade (Balfanz & Byrnes, 2012).

Functional profiles of school attendance problems

Many schools and school-based professionals that utilize tiered frameworks for academic, behavioral, and social issues also rely heavily on functional analysis and functional behavioral assessment practices to provide individualized student support (McCurdy et al., 2016; Simonsen & Sugai, 2013). At Tier 1, this may include a focus on school-wide antecedents or predictors of problem behavior, delineating appropriate and nuanced consequences for a behavior depending on its function and severity, and adjusting expectations across contexts and personnel (Crone, Hawken, & Horner, 2015). At Tier 2, this may include selecting and monitoring social and behavioral interventions for students on the basis of the function of their behavior (Reinke, Stormont, Clare, Latimore, & Herman, 2013). At Tier 3, this may include a more detailed assessment of multiple functions and replacement behaviors as well as more complex environmental change (Scott & Cooper, 2013).

Kearney and colleagues (e.g., Gonzálvez et al., 2019; Kearney & Graczyk, 2014; Kearney & Silverman, 1996) developed various aspects of a functional model of school attendance problems designed to apply particularly to school refusal behavior (i.e., child-initiated school attendance problems). This model focuses on key variables or functions that serve to maintain or reinforce school attendance problems and was designed primarily as a clinical approach for Tier 2-type school attendance problems. The postulated primary functions in the model include refusal to attend school to (1) avoid school-based stimuli that provoke a general sense of negative affectivity (i.e., aspects of both anxiety and depression), (2) escape aversive social and/or evaluative situations at school, (3) seek attention from significant others such as parents, and/or (4) pursue tangible rewards outside of school such as time with friends.

The first two functions refer to school refusal behavior maintained by negative reinforcement, whereas the latter two functions refer to school refusal behavior maintained by positive reinforcement. A profile of the relative strength of each functional condition is generally recommended during case analysis (Kearney, 2019). A key advantage of the functional model is its clear linkage to specific prescriptive treatment packages that include child-, parent-, and family-based interventions as well as Tier 3 interventions as needed (Kearney & Albano, 2018). The treatment packages are also designed to be flexible enough to be adapted to a variety of cases and locations, and indeed have been across educational, mental health, and medical settings (e.g., Hannan, Davis, Morrison, Gueorguieva, Tolin, 2019; Rohrig & Puliafico, 2018; Thastum, Johnsen, Silverman, Jeppesen, Heyne, & Lomholt, 2019; Tolin et al., 2009).

Another key aspect of the functional model is its amenability to support the study of various dimensions or profiles of youth with school attendance problems. Researchers have demonstrated across numerous studies that functions of school refusal behavior relate to different patterns of depression, anticipatory and school-based performance anxiety, stress, positive/negative affect, sleep problems, and social functioning (e.g., Fernández-Sogorb, Inglés, Sanmartín, Gonzálvez, & Vicent, 2018; Gonzálvez et al., 2018, 2019; Hochadel, Frölich, Wiater, Lehmkuhl, & Fricke-Oerkermann, 2014; Kearney, 2002; Richards & Hadwin, 2011; Sanmartín et al., 2018). Others have related the functions to clusters of absentee youth (Gallé-Tessonneau et al., 2019) and family environment types (Kearney & Silverman, 1995). In addition, functions of school refusal behavior may be superior to forms of behavior in predicting absenteeism severity (Kearney, 2007).

A functional model of school refusal behavior does carry limitations, however. As noted, the model is meant to apply primarily to Tier 2 (and perhaps to early warning signs evident in Tier 1) school refusal behavior and thus less to more chronic and severe school absenteeism or to cases primarily initiated by other entities (Kearney, 2016). In addition, the model is not necessarily applicable to all countries and cultures, though many have found analogous features in their locales (e.g., Brandibas et al., 2004; Kim, 2010; Seçer, 2014). In addition, some erroneously conflate specific assessment devices constructed to assist the functional model with the broader model itself, which is supposed to be based on a comprehensive analysis of maintaining variables (Kearney & Tillotson, 1998).

Summary

Dimensionally-oriented approaches to SA/A may help account for the considerable heterogeneity of this population by capturing a wide range of attendance/absenteeism expressions, prevention and intervention strategies, risk/contextual factors, absenteeism severity and developmental levels, and functional profiles of key maintaining factors. Dimensional approaches do consider school attendance as much as absenteeism and are helpful in informing treatment approaches for SA/A. As with categorical approaches, however, considerable barriers exist to implementing dimensional approaches in schools and other pertinent settings. In addition, dimensional approaches to SA/A will also have to adapt to rapid advancements in education and technology in future years.

General Summary

The plethora of conceptual approaches to SA/A is certainly a phenomenon worth celebrating. Researchers, educators, clinicians, and stakeholders such as parents have contributed immensely to the study and understanding of this complex population. Such study has involved definitions, classification systems, assessment protocols, and intervention strategies designed, in the end, to help children and adolescents attend school and to achieve better outcomes in adulthood. We salute all of those who have dedicated their time and careers to improving the lives of these students.

Part 1 of this two-part review concentrated on a broad classification and description of contemporary approaches to SA/A along categorical and dimensional orientations. Each orientation carries distinct advantages and disadvantages, a not uncommon circumstance across various problems and disorders that affect youth. Though meant to be comprehensive, this review focused on the primary methods of differentiating school attendance problems. Many nuanced distinctions based on multilevel and other statistical modeling should be noted, and many special circumstances such as intense school violence or extreme poverty likely override the distinctions mentioned here. In addition, prevention and intervention were not a primary focus of this part of the review, but are explored in greater depth in the second part of this review.

As suggested by several scholars, adopting both categorical and dimensional approaches to the study of complex and heterogeneous phenomena may be advisable. Such a juxtaposition has the potential advantage of identifying general categorical rules and cut-points for distinguishing broad groups of behavior as well as specific dimensions that are useful for providing data to adjust these cut-points along various spectra. Part 2 of this two-part review thus focuses on a possible pathway toward reconciling contemporary categorical and dimensional approaches to SA/A in this manner. This pathway also represents a heuristic framework as the field of SA/A grapples with challenges to dissemination and implementation as well as future changes in education and technology.

Reconciling Contemporary Approaches to School Attendance and School Absenteeism: Toward Promotion and Nimble Response, Global Policy Review and Implementation, and Future Adaptability (Part 2)

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Abstract

As noted in Part 1 of this two-part review, school attendance is an important foundational competency for children and adolescents, and school absenteeism has been linked to myriad short- and long-term negative consequences, even into adulthood. Categorical and dimensional approaches for this population have been developed. This article (Part 2 of a two-part review) discusses compatibilities of categorical and dimensional approaches for school attendance and school absenteeism and how these approaches can inform one another. The article also poses a multidimensional multi-tiered system of supports pyramid model as a mechanism for reconciling these approaches, promoting school attendance (and/or prevention of school absenteeism), establishing early warning systems for nimble response to school attendance problems, assisting with global policy review and dissemination and implementation, and adapting to future changes in education and technology.

Introduction

The field of school attendance and absenteeism (SA/A) remains, as it has always been, at various crossroads. Categorical and dimensional approaches to conceptualizing SA/A are manifold, and each approach has its own validity for defining, classifying, and providing assessment and prevention/intervention recommendations for this population (see Part 1 of this two-part review; Kearney, Gonzálvez, Graczyk, & Fornander, 2019). Categories generally refer to dichotomies and distinctions to identify groups, whereas dimensions generally refer to fluid or latent constructs arranged along various spectra or continua. Key categorical dichotomies and distinctions of SA/A include school refusal-truancy, excused-unexcused absences, school withdrawal and school exclusion, acute-chronic duration, and diagnostic categories. Key dimensional aspects of SA/A include defining school attendance and its problems along a continuum, multi-tiered system of supports for preventative and intervention strategies arranged according to student need, risk/contextual factors, absenteeism severity, developmental level, and functional profiles of school attendance problems.

The development of categorical and dimensional approaches to better understand a particular phenomenon is not unique to the field of SA/A; indeed, such bifurcation is a common aspect of the study of many different child behavior problems such as anxiety and mood disorders, developmental disorders, and attention-deficit/hyperactivity and conduct disorders (Elton, Di Martino, Hazlett, & Gao, 2016; Ghio et al., 2015; Hankin et al., 2017; Sprafkin, Steinberg, Gadow, & Drabick, 2016; Wakschlag et al., 2015). A key task moving forward will be to draw from the validity of all approaches to design a framework for SA/A that can facilitate the promotion of school attendance, nimble responses to emerging school absenteeism, effective policy review across jurisdictions, wide dissemination to various locations and settings, and adaptation to future, rapid changes in education and technology.

As noted in Part 1 of this review, Coghill and Sonuga-Barke (2012) stated that both categorical and dimensional approaches can coexist within a given phenomenon by serving different but equally useful purposes. Both categorical and dimensional approaches can be applied to a given heterogeneous construct. Categories are useful for providing general rules and cut-points for distinguishing broad groups of behavior, and dimensions are useful for providing data to adjust these cut-points along various spectra such as age, gender, temperament/behavior, developmental level, and setting to improve the categorical rules. Categorical distinctions can be useful descriptors of a particular current state, and dimensional profiles can be used to determine if that categorical state changes in degree of intensity (e.g., to nonproblematic or to more problematic) over time to inform treatment, longitudinal, and prognostic analyses. Categories and dimensions together can thus form a synergistic and breathable system that allows for considerable adaptation to future scientific and other advances (Hudziak, Achenbach, Althoff, & Pine, 2007).

Over the next sections of this article (Part 2 of a two-part review), we discuss a possible pathway toward reconciling contemporary categorical and dimensional approaches to SA/A. This discussion initially involves sample compatibilities across extant categories and dimensions of SA/A and how these constructs might be blended or matched with one another. This section focuses on pertinent or prominent examples and is not an exhaustive review of all possible affinities. This discussion then includes a multidimensional, multi-tiered system of supports (MTSS) pyramid model that may be used as a framework to include various categorical-dimensional aspects of SA/A. Finally, as mentioned, we explore how such a model could enhance promotion of school attendance and/or prevention of school absenteeism, expedite nimble clinical and other responses to emerging absenteeism via early warning system development, assist in policy review and dissemination across jurisdictions and disciplines, and adapt to future and rapid changes in education and technology. We emphasize that the framework presented here is a heuristic one, not meant to be necessarily optimal or capstone in nature, but rather one designed to help spur the field toward reconciliation, common language, and advancement. We fully expect and hope that the framework will evolve over time.

Compatibilities of Categories and Dimensions of SA/A

Compatibilities of categories and dimensions of SA/A (described in Part 1 of this two-part review) can be described in two main ways. First, many categorical approaches for SA/A actually have many dimensional features, and many dimensional approaches for SA/A actually have many categorical features. Second, many categorical and dimensional approaches for SA/A have striking similarities that may indicate general agreement about a particular construct, and refer to that construct from somewhat different perspectives. The examples provided next include both ways of describing compatibilities among categories and dimensions of SA/A.

Categories of SA/A with dimensional features

As mentioned in Part 1 of this review (p. 3), truancy is one of the most venerable constructs in the field of SA/A. From a categorical perspective, truancy may refer to illegal, unexcused school absence without parental knowledge or sanction (Gentle-Genitty et al., 2015). From a dimensional perspective, as noted in Part 1 of this review (p. 4), researchers have found many profiles of truancy along academic status, disability, location, race/ethnicity, in- and out-of-school activities, individual-group-orientation, premediated-spontaneous initiation, and parental academic involvement, among many other variables. Gentle-Genitty and colleagues

(2015) noted as well that categorical definitions of truancy often involve dimensions of absenteeism along time such as arriving late to school, missing a class, and missing a full school day, similar to the definitional spectrum of SA/A presented in Part 1 (p. 7).

Truancy as a category and truancy as a multidimensional construct are compatible notions. A categorical premise of lack of parental knowledge and sanction in truancy, for example, can be informed by various dimensional subtypes to boost its validity and enhance a greater intricacy to this distinction. For example, Keppens and Spruyt (2017) found that parental knowledge of a truant event was a highly nuanced construct that reflected lack of parental knowledge with expectation of parent distress (41.7%), lack of parental knowledge without expectation of parent distress (5.7%), parental knowledge with approval (34.5%), and parental knowledge without approval (18.1%). Truancy as a categorical and dimensional construct is also represented in research regarding forms and functions of SA/A. Researchers who study SA/A categorically generally examine forms of truant behavior such as externalizing problems, whereas researchers who study SA/A dimensionally generally examine functions or factors that maintain school refusal behavior such as pursuit of tangible rewards outside of school (Haight, Kearney, Hendron, & Schafer, 2011; Iverson, French, Strand, Gotch, & McCurley, 2016; Walter, von Bialy, von Wirth, & Doepfner, 2017). Both research avenues, however, gravitate toward older youth with less school-based anxiety (Dembo, Wareham, Schmeidler, & Winters, 2016).

As mentioned in Part 1 of this review (p. 3), school refusal often refers to another child-initiated form of school absenteeism. From a categorical perspective, school refusal may refer to emotional distress and reluctance to attend school (Elliot & Place, 2019). From a dimensional perspective, as noted in Part 1 (p. 4), researchers have found many profiles of school refusal along various spectra (e.g., Finning et al., 2018, 2019). Gallé-Tessonneau and Gana (2018), for example, found several main clusters of youth with school refusal involving anxiety and fear of confrontation, adolescent-parent relationships, interpersonal relationship difficulties, and coping difficulties that associated closely with functional dimensions or profiles. Researchers who study SA/A categorically generally examine forms of behavior such as anxiety, depression, and somatic complaints (Jones, West, & Suveg, 2019). Researchers who study SA/A dimensionally generally examine functions or factors that maintain school refusal behavior such as avoidance of negative affectivity and escape from aversive social and/or evaluative situations (Haight et al., 2011; Richards & Hadwin, 2011). Both research avenues, however, gravitate toward youth with more school-based distress (Havik, Bru, & Ertesvåg, 2015).

Other categorical constructs for SA/A also have dimensional features. For example, the construct of school withdrawal, or parent-initiated school absenteeism, includes a spectrum of parent behaviors such as knowledge, acquiescence, consent, approval, and accommodation, or more passive to more active responses (Kearney & Albano, 2018; Marin, Anderson, Lebowitz, & Silverman, 2019). Similarly, school exclusion or school-initiated absenteeism can involve a spectrum of lawful or unlawful administrative responses such as loss of privileges, early school departure, detention, in-school suspension, out-of-school suspension, restorative or other interventions in another location, alternative educational placement, and expulsion as well as duration of the exclusion (Valdebenito, Eisner, Farrington, Ttofi, & Sutherland, 2018). In addition, Birioukov (2016) sought to reframe the categorical dichotomy of excused-unexcused absences along broader distinctions (i.e., voluntary and involuntary) with varying explanations. Voluntary absence, for example, might encompass more student agency involving spectra along motivation to attend school and perceptions of school as a hostile environment. Involuntary absence might encompass more contextual influences that affect a student's ability to attend school and include spectra along life conditions, opportunities for academic advancement, and access to education (see also Part 1 of this two-part review, p. 5).

Dimensions of SA/A with categorical features

As mentioned in Part 1 of this review (p. 10), a functional model of school refusal behavior focuses on dimensions or profiles of the relative strength of maintaining factors for school refusal behavior. The model was originally designed as a clinical strategy to help mental health professionals utilize descriptive and experimental functional analyses to identify a particular prescriptive treatment tailored to these maintaining factors (Kearney & Silverman, 1990). Youth may refuse to attend school to (1) avoid school-based stimuli that provoke a sense of negative affectivity (anxiety and depression), escape from aversive social and/or evaluative situations at school, (3) pursue attention from significant others, and/or (4) pursue tangible rewards outside of school. The functions were based on wide parameters of negative and positive reinforcement (Kearney, 2001).

In this functional model, a dimensional profile of maintaining factors is derived via a comprehensive assessment that includes descriptive measures, rating systems, behavioral observations, and formal hypothesis testing, among other means. Some erroneously equate one descriptive instrument with the broader functional model, but the functional distinctions can be measured in many ways to derive detailed and nuanced clinical profiles of each (Kearney & Tillotson, 1998). Indeed, the functional model was specifically designed to be flexibly applied to different clinical and educational settings to account for differences in local practices as well as the heterogeneity of school attendance problems and to enhance the treatment utility of assessment (Nelson-Gray, 2003). With respect to the latter, a primary function based on relative strength to the others may be categorically chosen as a starting point for prescriptive intervention

(Kearney & Silverman, 1999). A categorical nature of the functional model is further reflected in research work examining differences between the functions (e.g., Haight et al., 2011). As such, the model is a flexible, prototypical categorical-dimensional approach for SA/A and has been generally utilized and studied in this manner (e.g., Elsherbiny, 2017; Gresham, Vance, Chenier, & Hunter, 2013; Lyon & Cotler, 2009; Nuttall, & Woods, 2013).

Similarly, a multi-tiered system of supports (MTSS) model of SA/A (see Part 1 of this review, pp. 7-9) involves several dimensional continua with respect to absenteeism chronicity and severity as well as degree of risk and contextual factors generally associated with increasingly higher levels of absenteeism. An MTSS model of SA/A also assumes a spectrum of needed supports for youth and their families ranging from (1) system-wide or universal preventative approaches to (2) targeted interventions for mild to moderate school attendance problems to (3) intensive interventions for chronic and severe absenteeism (Kearney, 2016). The spectrum-based nature of MTSS is designed in part to enhance feasibility for, and thus applicability to, various educational and other settings (Stoiber & Gettinger, 2016).

A key component of MTSS models, however, is a categorical tier-based structure with ostensibly clear demarcations between each level of supports. Specific demarcations are important for understanding when to shift the focus of intervention to a higher (or lower) tier. Within a reading context, for example, standardized assessment protocols may be utilized to identify students with specific comprehension or word decoding problems that warrant Tier 2 or Tier 3 intervention (Leonard, Coyne, Oldham, Burns, & Gillis, 2019). In addition, teacher-based screening and office disciplinary referrals for behavior may indicate a failed intervention and thus a marker for movement to a different tier (Naser, Brown, & Verlenden, 2018). As such, assessment profiles inform movement from one categorical tier to another. With respect to an

MTSS model for SA/A, identifying when a child could move from one tier to another will involve expanded research into tier-based demarcations that may help inform intervention assignment (Fornander & Kearney, 2019a, b) (see also later sections).

Other dimensions of SA/A, including those within an MTSS model, have been examined categorically as well. Risk and contextual factors of SA/A, for example, are commonly studied or grouped into child-, parent, family-, peer-, school-, community-, cultural-, and even government-based distinctions, as well as how these distinctions change across locations (Correia & Marques-Pinto, 2016; Kearney, 2008; Lamb, Markussen, Teese, Sandberg, & Polesel, 2010; Sahin, Arseven, & Kilic, 2016). Researchers examine these risk factors via spectra of accumulated risk as well as via statistical modeling to compare the contributed risk of each group (Chen, Culhane, Metraux, Park, & Venable, 2016; Chung & Lee, 2019; Goodrich, Castellano, & Stefos, 2017; Sansone, 2019). Similarly, researchers have examined absenteeism severity both as dimensional ranges and as categorical distinctions (Skedgell & Kearney, 2016, 2018; Stempel et al., 2017).

Categories and dimensions of SA/A: Informing one another

Categorical and dimensional approaches to SA/A have many compatibilities as well as overlapping qualities and purposes. As noted earlier, categorical distinctions of SA/A, which have traditionally suffered from considerable ambiguity and limited construct validity (Part 1 of this review, p. 6), may be better informed by common and empirically-based higher-order dimensions. Such dimensions may help identify functional analytic and temporal aspects to improve the practical nature of different categories in clinical and educational practice (Brown & Barlow, 2009). For example, identifying risk or behavioral marker profiles would help improve a distinction between Tier 1 prevention and Tier 2 early intervention (Mitchell, Stormont, &

Gage, 2011). In addition, identifying specific pathognomonic or at least assident features of various SA/A categories may ultimately come from examining ranges or profiles of constructs such as avoidance, emotion regulation, cognitive features, temperament, parent responses, family environment dynamics, association with deviant peers, school climate, and perhaps even biopsychosocial or bioecological aspects (Caron, Weiss, Harris, & Catron, 2006; Gottfried & Gee, 2017; Rothbart, & Posner, 2015). In the next section, we posit a multidimensional multi-tiered system of supports pyramid model of SA/A that allows space to explore these research avenues while simultaneously charting preventative and intervention processes for immediate dissemination and implementation.

A Multidimensional Multi-Tiered System of Supports Pyramid

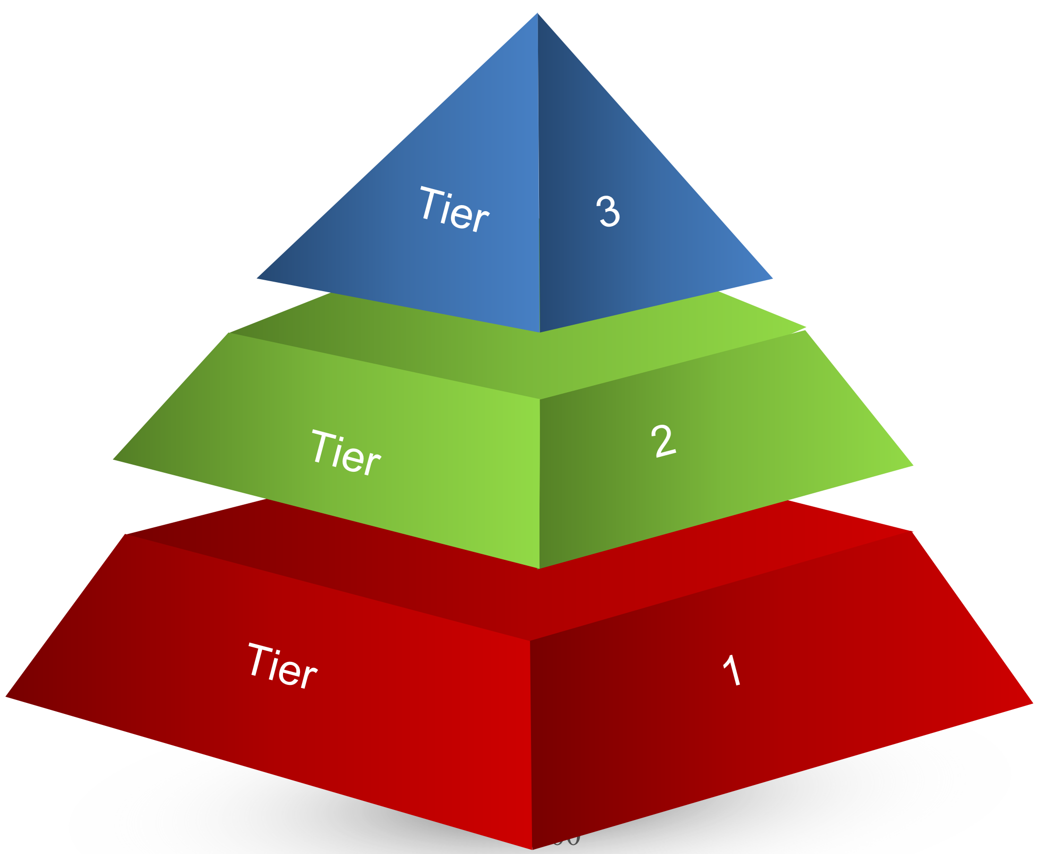
Multi-tiered system of support (MTSS) models, including Response to Intervention and Positive Behavioral Interventions and Supports/School-wide Positive Behavior Support, are often represented via one-dimensional triangles as illustrated in Part 1 of this review (p. 8). As discussed, these approaches represent multiple tiers of preventative and intervention strategies for various academic, social, and behavioral issues. These tiers are arranged along a continuum of needs of support targeted toward all students (prevention), some percentage of students (early intervention), and some lesser percentage of students (intensive intervention). Kearney and Graczyk (2014) were the first to apply these principles to SA/A (see Part 1 of this review for greater detail, pp. 7-9).

A key constraint of the one-dimensional triangle representation of MTSS is that it assumes considerable homogeneity among the population at hand, such as all children in a particular elementary school who are learning to read or all adolescents in a particular high school with a disruptive behavior resulting in an office disciplinary referral (Sugai & Horner, 2009). As such, preventative and intervention strategies are usually geared in similar fashion, albeit with some flexibility based on nuanced factors such as the function of misbehavior, intensity of punitive response, and responding administrator (e.g., teacher, dean) (Crone, Hawken, & Horner, 2015). Such an approach appears reasonable at Tier 1 where the focus is on promoting a certain phenomenon (e.g., ability to read) and/or preventing a certain phenomenon (e.g., classroom disruption) for all (and generally similar) students in a given setting. The use of communal approaches at Tier 2 and Tier 3, however, may be less efficacious for as heterogeneous and complex a population as students with school attendance problems.

A progressive conceptual framework for an MTSS approach is to emphasize the notion of a multi-dimensional (and thus multi-sided) pyramid to account for greater heterogeneity as well as clinical and research avenues for a certain population (Dulaney, Hallam, & Wall, 2013). An example is a multi-tiered, multi-domain system of supports (MTMDSS) model (Hatch, Duarte, & De Gregorio, 2018). In an MTMDSS model, various tiers of support are associated with multiple domains such as school counselor efforts to address, simultaneously and yet differently, the academic, career readiness, and social/ emotional needs of their students (Hatch, Triplett, Duarte, & Gomez, 2019). These tiers of support remain similar to the 3 levels of an MTSS model but the presence of multiple sides means the tiers can apply variously and flexibly to different domains.

The basic conceptual structure of a multi-dimensional pyramid may fit well with the multifaceted nature of SA/A. In this structure (Figure 15), different sides of a multi-dimensional pyramid could reflect different sets of key categorical-dimensional domains of SA/A. Such domains, among many others, could involve (1) child-, parent-, or school-initiated/oriented school attendance problems, (2) different dimensions of categories such as truancy, (3) functional or risk and protective factor profiles or clusters, (4) school attendance problems in preschool, elementary, middle, and high school students, and (5) schools at low, medium, and high risk for absenteeism. In addition, multi-dimensional pyramids could be developed and tailored to individual jurisdictions with different set points for movement across the tiers. Such pyramids would also allow for better cross-disciplinary work and enhance creativity and innovation about how this population is conceptualized. A multi-dimensional pyramid could vary according to the number of domains desired (e.g., 4, 6 sides) as well. Most importantly, this approach mandates the development of preventative and intervention strategies for each tier no matter what domains are used.

Figure 15. Illustration of a sample multidimensional multi-tiered system of supports pyramid model for school attendance and school absenteeism.



As an example, Lyon and Cotler (2009) juxtaposed functional dimensions along microsystem, mesosystem, and exosystem levels of intervention for school refusal behavior. Microsystem interventions address more direct, proximal, or immediate influences on school attendance problems, and specific aspects within the microsystem can be linked to specific functional dimensions. In this framework, (1) peer microsystem interventions (e.g., mentoring, social skills) might best be linked to avoidance of social/evaluative situations and pursuit of tangible reinforcement; (2) family microsystem interventions (e.g., contingency management, contracting) might best be linked to avoidance of social/evaluative situations, pursuit of parental attention, and pursuit of tangible reinforcement; and (3) school microsystem interventions (e.g., incentive programs, academic support) might best be linked to avoidance of negative affectivity, avoidance of social/evaluative situations, and pursuit of tangible reinforcement.

Mesosystem interventions address connections between settings most relevant to a child such as parent-school official contacts. In this framework, mesosystem interventions (e.g., school engagement and parental involvement initiatives) might best be linked to pursuit of parental attention and pursuit of tangible reinforcement. Exosystem interventions (e.g., policy changes, statutes) address more distal social structures or settings that have an indirect influence on school attendance problems, and may best be linked to all functions of school refusal behavior. The authors also discussed macrosystem influences, or societal or cultural/subcultural influences that envelop other levels (in this case, those involving school absenteeism). Such influences may include, for example, shifts in economic opportunities, globalization, migration/immigration, and labor markets that impact school dropout rates (Brewer & McEwan, 2010; Coxhead & Shrestha, 2017).

Lyon and Cotler's (2009) approach, a key prelude to the multi-tiered frameworks discussed here and in other articles (see also Lyon & Bruns, 2019), emphasized the notion of multifaceted tiers that each reflected multiple domains related to school attendance such as functional profiles, contextual factors, and intervention types and levels. In addition, the authors worked to supersede traditional notions of school refusal and truancy, emphasize how multi-systemic interventions can augment personalized clinical treatment approaches, and encourage the expansion of tailored strategies to best serve different ethnic and cultural groups, a process that remains largely underdeveloped in the SA/A field even today. One omission of Lyon and Cotler's (2009) approach was the notion of preventative practices to proactively address multi-system factors leading to school attendance problems, a topic we turn to next.

Base of the pyramid: Promoting school attendance

The notion of a multidimensional MTSS/MTMDSS pyramid model carries some potential advantages as a heuristic for SA/A. First, the notion of a multidimensional pyramid implies a common base involving children and adolescents who are attending school without difficulty. The base of a pyramid is necessarily broad and strong and critical for the support of the upper tiers. As such, the base of the pyramid is the most fundamental aspect of the structure, and must be well maintained. The notion of a pyramidal base thus means that all stakeholders in the field of SA/A begin with the common premise that school attendance is valued and that promoting school attendance (and/or preventing school absenteeism) must be the foundation for all other efforts in this area.

Second, the notion of a strong (and larger) pyramidal base means that most efforts in this area will need to focus on promoting school attendance and not simply on reducing absenteeism. With respect to SA/A, this means that school districts, health and mental health professionals, and lay persons must invest significant resources and efforts into Tier 1 practices to prevent youth from entering Tiers 2 and 3. All too often, stakeholders in this field concentrate on policies, procedures, sanctions, treatments, and other methods to react to student absenteeism as opposed to engaging in measures to proactively maintain and boost school attendance. The notion of a multidimensional base means that proactive, preventative efforts must be emphasized and can be tailored to individual schools, jurisdictions, and cultures.

Third, the notion of a strong pyramidal base means that researchers must focus as much on protective and promotional factors toward high school completion (or its equivalent) as on risk factors and other aspects of school absenteeism. Some continue to invest heavily in incremental distinctions of youth with school absenteeism with little investment toward identifying those who do complete school. Indeed, the absence of risk is not the same as the presence of growth. In addition, many researchers tend to focus on the negative consequences of school absenteeism and dropout and less so on the benefits of graduation. A better understanding of such protective factors would greatly inform prevention science in this and related areas (Kieling et al., 2011; Lösel & Farrington, 2012).

Zaff and colleagues (2017) reviewed literature on factors that promote high school graduation, with a particular focus on dimensions of positive youth development as well as proximal and distal influences within a student's ecology. Such protective and promotive factors included malleable assets, or those potentially sensitive to intervention, and upstream factors, or those more systemic and likely more difficult to modify. The authors made an astute point that simple lack of risk factors in a particular child does not necessarily imply that the child is thriving or that development is optimized. Instead, researchers and others must focus on variables that actively promote educational attainment, not simply on those that predict school absenteeism and dropout.

Individual student factors found most to predict high school graduation or continued school enrollment included intrinsic motivation to achieve positive educational outcomes, enhanced school engagement, student expectations for academic attainment, and internal locus of control. School engagement can come in many forms, and the authors found that high levels of behavioral (e.g., attending school, completing assignments), emotional (e.g., connection with school, enjoying school), and cognitive (e.g., strategic learning, intellectual curiosity) were most related to academic success and graduation. Of these variables, particularly salient predictors included attendance, social and academic engagement, and arts and athletic participation. Expectations for, and perceived control of, positive academic outcomes were potent predictors as well. Effect sizes were small to moderate.

Parent factors found most to predict high school graduation or continued school enrollment included parental academic involvement and parent-child connection. The former may be associated with attending school-based meetings and conferences, participating in school-based organizations, communicating regularly with school officials, assisting with homework, and setting clear rules about homework and maintaining a good grade point average. Many of these effects remained even after controlling for demographic and school composition variables. Parental social support and regular parent-child communication comprised the parent-child connection construct. Effect sizes for parent influences were generally small. Peer-related factors were more limited and included positive peer norms, or expectations of what behaviors are valued within a particular group of friends. This may include enhanced expectations for maintaining grade point average and for valuing education. Effect sizes for peer influences were generally small.

School-related factors found most to predict high school graduation or continued school enrollment included positive student-teacher relationships, smaller schools, participation in school-based extracurricular activities, and career and technical education. Positive student-teacher relationships can include respectful interactions, teacher interest in students, and student belief in teacher competence. This may relate to smaller schools as well, where teachers and students may be more knowledgeable of one another. Extracurricular activities, including community service participation, may relate specifically to social competence, educational aspirations, and sense of agency among students. Career and technical education opportunities positively impact continued school enrollment in particular. Effects sizes for school variables ranged from small to large.

Finally, the primary community-related factor found most to predict high school graduation or continued school enrollment was participation in out-of-school time programs, or those collection of programs focused on community service, social-emotional learning, and academic enrichment. The authors concluded that more research is needed on how all of these protective factors interact with one another to enhance the trajectory toward graduation, how the factors operate differently across students and contexts, and how risk and demographic factors moderate the effect of assets to promote graduation (Zaff et al., 2017).

Zaff and colleagues' (2017) efforts also reveal the value and utility of examining various key dimensions or domains of functioning to inform categorical distinctions between nonproblematic (Tier 1) school attendance and problematic (Tier 2) school absenteeism, and thus preventative targets. Indeed, effective school dropout prevention programs are often based on dimensions of student engagement with school, parental involvement, and school climate (Wilson, Tanner-Smith, Lipsey, Steinka-Fry, & Morrison, 2011). In addition, effective components of programs designed to increase school completion are often arranged in dimensional levels of support that involve students (e.g., academic tutoring, social skills instruction, character development, leadership training, work experience, attendance incentives), schools (e.g., smaller class sizes, anti-bullying, wider access to mental health support), and policy changes (e.g., reduced stigmatization and use of exclusionary discipline for absenteeism, support for Tier 1 approaches) (Balu & Ehrlich, 2018; Freeman & Simonsen, 2015; Freudenberg & Ruglis, 2007). Utilizing dimensions or domains of functioning to inform categorical distinctions between nonproblematic (Tier 1) school attendance and problematic (Tier 2) school absenteeism also has implications for early warning systems and nimble clinical and other responses to emerging school attendance problems, discussed next.

Second tier of the pyramid: Early warning and nimble response

The notion of a multidimensional MTSS/MTMDSS pyramid model also implies that screening and immediate, nimble response to early warning signs or Tier 2 cases of emerging school absenteeism must be a priority no matter the domain structure utilized on the sides of a pyramid. For example, domains of school attendance problems across elementary, middle, and high school levels must juxtapose with individualized, tailored strategies to identify these problems within the resources and logistical constraints of each domain. This may mean an attendance officer in an elementary school who can call parents immediately each day upon learning of a student absence, a school attendance team (e.g., guidance counselor, dean, school-based social worker) in a middle school that regularly reviews attendance data and intervenes with a family prior to a legal tripwire for truancy, and an integrated first period teacher-attendance team in high school that coordinates information about attendance, disciplinary referrals, and course grades (Kearney, 2016; Rumberger et al., 2017). The ability to nimbly respond to these problems, particularly in school settings, depends heavily on valid early screening methods for SA/A in children and adolescents.

Screening for school attendance problems has occurred in various ways that include both ancillary and direct approaches. With respect to the former, for example, Gall and colleagues (2000) described a screening process at a school-based health center that included school absence as well as a number of psychosocial and academic variables. Students identified with emotional and behavioral problems and referred for mental health services decreased their school absences nearly 50%, and tardiness instances 25%. Mechanisms of action for this effect may include enhanced resilience and health status and behaviors (Walker, Kerns, Lyon, Bruns, & Cosgrove, 2010). Others have screened for ancillary variables such as office disciplinary referrals or health problems such as asthma as markers for attendance problems (Caldarella, Young, Richardson, Young, Young, 2008; Moricca et al., 2013; Weismuller, Grasska, Alexander, White, & Kramer, 2007).

Recent endeavors have focused more on direct screening approaches for school attendance problems that include both categorical and dimensional aspects. Early warning systems that focus specifically on attendance, behavioral data/suspensions, and course grades have been found to consistently identify 50-75% of future school dropouts before the event occurred. These categories have been further informed by dimensional data indicating that attendance rates under 85-90%, two or more suspensions, and two or more semester course failures in any subject are particularly pertinent indicators and should be part of a customized multi-tiered response system (Balfanz & Byrnes, 2019; Thomas, 2017). Such data could be collated via an online monitoring system, and many school districts utilize software applications to immediately inform parents of an absence as well as course assignments and grades (e.g., https://www.infinitecampus.com/audience/parents-students). Researchers have also utilized text and mobile telephone communications to immediately identify and mitigate school absences (Cook, Dodge, Gifford, & Schulting, 2017; Smythe-Leistico & Page, 2018) within a dimensional multi-tiered intervention framework.

Other direct screening approaches for school attendance problems focus on spreadsheets listing student demographics, attendance status, behavior, course performance, and interventions (Rumberger et al., 2017), brief pediatric consultations (Katz, Leith, & Paliokosta, 2016), online self-report methods (Pflug & Schneider, 2016), and checklist methods for categories of absences mixed with level of absenteeism severity (Heyne, Gren-Landell, et al., 2019; Kearney, 2008). A nimble response to a child's absence from school would benefit from immediate knowledge of whether the absence was due to school exclusion such as suspension or alternative educational placement or home instruction, school-based threat such as bullying, parent-based school withdrawal, legitimate reason such as illness or poor weather, or a child-based anxiety, mood, or conduct problem (Ingul, Havik, & Heyne, 2019). Basic screening approaches have advantages for limiting the burden on school officials, though early warning systems that are too parsimonious may have limited validity (O'Cummings & Therriault, 2015; Sansone, 2019).

More nuanced early warning systems have thus been developed. Chu and colleagues (2019) developed an online early detection system for school attendance problems, with a particular focus on teachers, administrative assistants, and school counselors as attendance monitors and trackers. The authors utilized a categorical cutoff of 5 absences (or 2.78% in a 180-day school year) that included dimensions of absenteeism severity ranging from full days missed to instances of tardiness to early departures from school. School attendance problems were assessed at the end of each of four marking periods throughout the academic year. Yearly absences were more closely associated with an accommodation plan and having a sibling with similar attendance problems. Instances of tardiness were more closely associated with higher grade level, divorced or separated parents, and having a sibling with similar attendance problems. Early departures were more closely associated with male gender, newness to a school, and having a sibling with similar attendance problems.

Several researchers have also recommended machine learning and related predictive modeling methods to study large SA/A-based data sets to help inform such algorithms and early warning systems (do Nascimento, das Neves Junior, de Almeida Neto, & de Araújo Fagundes, 2018). Chung and Lee (2019), for example, utilized random forests in machine learning to predict student dropout among 165,715 Korean students. Key indicators included unauthorized absence, early leave, class absence, and lateness as well as various test scores and school experiences. School dropout was predicted most by several risk factors that included all forms of unauthorized school attendance problems. In addition, several protective factors were identified that included self-regulated activity, career development, club activity, and volunteer work. The authors recommended that homeroom teachers utilize such markers to mitigate risk and enhance protective factors via appropriate supports and interventions. Indeed, some have advocated for restructuring the role of the homeroom or first-period teacher to quickly identify an absent and transmit the information to a school attendance team member who immediately contacts parents (Lever et al., 2004).

Sansone (2019) also advocated for machine learning approaches to provide algorithms for predicting school dropout among 21,440 ninth-grade students. Key predictors selected by the statistical methods used included age, lack of important math and science courses, grade point average, and whether a student had ever been suspended or expelled from school. Other more secondary predictors included lack of plan to later enroll in college, parent contacted by school about poor attendance, and parent belief that the child will at best attain high school only. The author recommended identifying at-risk students based on these variables to identify effective academic and vocational approaches as well as informing parents of a particular student's risk level. The author concluded as well that early warning systems that are too parsimonious may lack reliability, and that identifying students at less risk for dropout may be as useful as identifying those at high risk.

More specific to school absenteeism, Kearney and colleagues (Fornander & Kearney, 2019a, b; Kearney, 2018; Skedgell & Kearney, 2018) conducted several studies utilizing ensemble and classification and regression tree (CART) analyses to identify demographic, academic, behavioral, and family factors that best differentiated school absenteeism at various severity levels. Skedgell and Kearney (2018) examined records from 316,004 students across elementary, middle, and high schools to identify academic and demographic variables that best predicted distinctions between <1% and 1+% absenteeism, <10% and 10+% absenteeism, and <15% and 15+% absenteeism based on differentiations sometimes recommended in the literature.

Four predictors that best differentiated youth at <1% and 1+% absenteeism severity levels included ethnicity (Hispanic, African American, Caucasian, biracial, American Indian, or Pacific Islander), grade point average (0.00-2.00), grade level (1, 2, 9, 10, 11, or 12), and Individualized Education Plan (IEP) eligibility. Three predictors that best differentiated youth at <10% and 10+% absenteeism severity levels included age (>15.5 years), ethnicity, and low grade point average. Four predictors that best differentiated youth at <15% and 15+% absenteeism severity levels included age (>16.5 years), ethnicity, low grade point average, and grade level (1, 6, 7, 8, 10, 11, or 12). Post hoc analyses were also conducted for developmental school levels. At the elementary school level, ethnicity and grades 1 and 2 were most predictive of all absenteeism severities. At the middle school level, ethnicity and IEP eligibility were most predictive of <1% and 1+% absenteeism, whereas ethnicity was most predictive of the other absenteeism severity levels. At the high school level, low GPA was most predictive of all absenteeism severity levels.

Fornander and Kearney (2019a, b) further used ensemble and CART analyses to examine predictors of various absenteeism severity levels (1+%, 3+%, 5+%, 10+%, 15+%, 20+%, 30+%, 40+%) in youth with school attendance problems referred for clinical services or to a truancy or family court. As with the demographic and academic variables described in the previous study, predictive risk factors tended to be more homogeneous at higher levels of absenteeism severity. These studies included analyses of family environment variables as well as internalizing symptoms of anxiety and depression.

With respect to family environment, higher levels of absenteeism (i.e., 15+%) were more closely related to lower achievement orientation, active-recreational orientation, cohesion, and expressiveness. Many findings were quite nuanced, however. For example, lower expressiveness was evident at less severe (3%, 5%) and more severe (20%, 30%) levels of absenteeism, though elevated expressiveness was predictive of 10+% absenteeism. In addition, family cohesion was not predictive at 1+% and 3+% absenteeism but less cohesion was more predictive of higher levels of absenteeism. Elevated conflict was more predictive of 5+% absenteeism severity, whereas lower conflict was more predictive of 10+% absenteeism severity.

In addition, less family control was more predictive of higher levels of absenteeism severity (20+%, 30+%).

With respect to internalizing symptoms, one consistent item that distinguished levels of higher from lower absenteeism severity was a depression item related to lack of enjoyment. Predictive items at 1% and 3% absenteeism were less informative than items at higher absenteeism levels. For example, endorsement of less anxiety was more predictive of higher levels of absenteeism severity, a finding similar to Skedgell and Kearney (2016) who found that very high levels of absenteeism were generally marked by less anxiety. This could mean that extensive absence from school mitigates anxiety at the time of assessment.

The nascent development of valid early warning systems of SA/A (as well as continuous screening devices) has tremendous potential for informing more nimble responses on the part of school officials. This is especially critical now that schools are a primary site of mental health care for most youth (Green et al., 2013; Lyon et al., 2019). Screening devices with set algorithms or rules would allow for nearly simultaneous assessment and intervention, such as quicker use of informed clinical, referral, and other strategies to mitigate emerging school attendance problems. Such devices may also help school officials triage or narrow the focus of these nimble responses, such as toward child, parent, and peer microsystems (Kearney, 2019; Lyon & Cotler, 2009). The studies also reveal a fine line between parsimony and validity, however, meaning that researchers must thread the needle of identifying informative early warning systems that are acceptable and not burdensome to school-based professionals.

Clusters of variables are likely more useful for deriving an algorithm to inform an early warning system for school attendance problems, including for categories of absences, than singular factors such as child internalizing behavior. Indeed, researchers in child psychopathology increasingly use item response theory and signal detection approaches to identify multiple dimensional spectra of normal and abnormal functioning (Wakschlag et al., 2019; White et al., 2017). These approaches would be particularly useful for identifying cutoffs and criteria, transdiagnostic constructs, and multi-system responses (Nigg, 2017) for school attendance problems most pertinent to a specific jurisdiction or culture. Such approaches could also help inform global policy review and dissemination and implementation practices for SA/A, discussed next.

Global Policy Review and Dissemination and Implementation

One of the most significant challenges for researchers of SA/A has been effective dissemination and implementation of conceptualization, assessment, and intervention approaches into schools, physical and mental health agencies, and the corridors of policy makers. Reasons for this are myriad and may include lack of consensus among scholars, the complexity and heterogeneity of this population, disconnect between disciplines, school resistance, and substantial administrative, logistical, legal, and other restrictions uniquely faced by school officials (Graeff-Martins et al., 2006; Kearney, 2003; Keppens & Spruyt, 2017). With respect to the latter, for example, many schools have been restricted by zero tolerance laws that mandate specific sanctions for absenteeism that may displace clinical and other approaches (Gage, Sugai, Lunde, & DeLoreto, 2013). Exclusionary discipline policies, reporting guidelines, legal definitions of truancy, and disincentives for early school response likely play a role in this process as well (Brouwer-Borghuis, Heyne, Vogelaar, & Sauter, 2019; Marchbanks et al., 2015). Of course, many jurisdictions and countries have no legal or other policy regarding school absenteeism whatsoever (UNESCO, 2012). Furthermore, statewide truancy policies appear unrelated to chronic absenteeism levels, and may actually be pernicious in that diverse students are subjected to more restrictive policies (Conry & Richards, 2018). Such policies also institutionalize the concept of truancy and thus color approaches taken for the problem (Spruyt, Keppens, Kemper, & Bradt, 2017).

Markussen and Sandberg (2011) noted that policy measures to address school absenteeism and dropout vary widely across countries, range from considerable to little impact, and are often affected more by economic shifts and labor markets. Still, the authors identified several policy measures across various countries that may have some impact on school absenteeism and dropout at system-wide levels, such as career guidance and counseling, income support for students, and vocational education and alternative educational programs. Markussen and Sandberg (2011) noted that these and other policy measures must be based on a deep understanding of local conditions, including the unique attributes of those with school absenteeism and dropout, as well as on a common commitment to developing better theory for addressing these issues within the context of each country. Global policy review with respect to school absenteeism must therefore focus on pruning counterproductive measures in addition to disseminating and implementing theoretical models that can be uniquely tailored to cross-cultural settings.

A multidimensional multi-tiered system of supports pyramid model of SA/A could be one such vehicle for policy review and dissemination. The model is consistent with whole-school reform models of education, and eschews policies and practices that focus on exclusionary discipline (and unlawful school exclusion), immediate referrals to legal and other outside agencies, tacit acceptance of low-performing students who leave school, inflexible curricula, and rigid standardized testing (Kearney, 2016). In addition, the model and associated algorithms can be flexibly and practically tailored to idiosyncratic differences related to local norms, calendars, and educational practices. The model is designed to be inclusive, simple, and easily adaptable to extant modes of service delivery in schools, which are key parameters of successful dissemination and implementation (Lyon & Bruns, 2019). In addition, the multidimensional model may be well positioned because it can dovetail with (1) already existing school-based multi-tier frameworks devoted to academic performance, school climate/positive school culture, social and emotional competencies, and career readiness, and (2) functional behavioral assessment practices, both of which are already understood and utilized by many school officials (Eklund et al., 2019; Freeman & Simonsen, 2015).

Lyon and colleagues (Cook, Locke, Waltz, & Powell, 2019; Lyon, Cook, Locke, Davis, Powell, & Waltz, 2019) iteratively adapted implementation strategies and recommendations from the healthcare sector to create a common nomenclature for such strategies that would be relevant to the educational sector. A total of 75 unique implementation strategies were compiled into several larger conceptual categories, which could apply generally to programs designed to promote school attendance and/or curb absenteeism (Lyon & Cotler, 2009). A full explication of these categories is beyond the scope of this article, but especially pertinent categories are briefly summarized next vis-à-vis a multidimensional model of SA/A.

One set of adaptations, "use evaluative and iterative strategies," referred in part to understanding the unique aspects of a given school context to identify potential barriers to implementation (and which school officials can best facilitate implementation), execute changes incrementally, establish clear goals and outcomes, develop monitoring systems with fidelity, obtain student and family feedback, and adjust practices as needed. Perhaps the most common school-based barriers to MTSS-based models include lack of daily and consistent use as well as poor linkage of data with action (Leonard et al., 2019). A multidimensional multi-tiered system of supports pyramid model of SA/A can be, however, amenable to simple feedback mechanisms, reliance on data-based decision-making, incremental employment within each tier, multiple stakeholder involvement, and consultation practices that may erode such barriers (Forman, & Crystal, 2015; Scott, Gage, Hirn, Lingo, & Burt, 2019). In addition, many clinical procedures to address school absenteeism at Tier 2 can be adaptively administered by school-based social workers, psychologists, and guidance counselors (Kearney, 2018, 2019).

Other sets of adaptations, "provide interactive assistance" and "adapt and tailor to context," referred in part to using a centralized system within a district to assist in implementation, pair school personnel together, identify ways a new practice can best be adapted to a given school context, utilize experts to inform implementation efforts, and integrate educational and administrative data across schools. A key advantage of a multidimensional multi-tiered system of supports pyramid model of SA/A is that many schools already utilize MTSS or related tier-based principles as a centralized system and may thus be more equipped and willing to absorb school attendance/absenteeism into their frameworks. Use of student review boards, district-wide task forces, and similar existing mechanisms at the system level for truancy may be helpful in this regard as well (Bye, Alvarez, Haynes, & Sweigart, 2010). In addition, MTSS models of SA/A rely on attendance teams involving multiple school officials that can be informed by research-based findings (e.g., early warning systems, tier demarcations) described in this review (Kearney, 2016). Others have also appealed for better sharing of attendance and graduation rates across schools in a given district to identify which contexts have been more successful with respect to school completion and how certain practices can be extrapolated (DePaoli et al., 2015).

Other sets of adaptations, “develop stakeholder interrelationships,” “support clinicians,” and “engage consumers” referred in part to developing partnerships internal and external to a school (e.g., university, school board) for training purposes, adding different disciplines as needed, providing real-time data regarding student outcomes, constructing educational materials regarding new practices, engaging with families to become active participants, and utilizing media to reach large numbers of people. MTSS models commonly employ school-community/research partnerships involving varied professionals from mental health and youth-serving systems (Weist et al., 2018). In addition, Chu and colleagues (2019) recommended the use of researcher-designed, publically available platforms for deriving real-time attendance and related data that could be available to districts nationally and internationally. Many schools are also moving toward more standardized data collection systems with respect to basic performance outcomes (e.g., attendance, office disciplinary referrals, course grades) in conjunction with new federal mandates (Egalite, Fusarelli, Fusarelli, 2017). As noted earlier, MTSS models also rely heavily on family and student engagement practices as well as educating parents about relevant school district policies regarding attendance and available resources (Kearney & Graczyk, 2014; Kearney, 2016).

Successful dissemination and implementation strategies for SA/A will likely have to include some level of absorption into what schools are already doing to address social, emotional, and behavioral competencies. Many/most schools already emphasize measurement, functional behavioral assessment, feasible multi-tiered approaches, and performance and student outcomes related to attendance, discipline, and academic progression (Lyon & Bruns, 2019). Schools are often motivated as well in an era of linked funding and mandates to improve attendance and graduation rates (DePaoli, Balfanz, Atwell, & Bridgeland, 2018). In addition, school-based professionals often coordinate efforts with mental health, medical, legal, social service, and other outside agencies to help implement wide-ranging approaches for SA/A (Kearney, 2016). Successful dissemination and implementation strategies for SA/A will also have to involve adaptation to future changes in education and technology, a topic discussed next.

Adaptability to the Future of Education and Technology

One of the biggest challenges for educators, researchers, clinicians, and others who study and address SA/A will be massive and rapid changes in education and technology over the next several decades. Any SA/A model will thus need to be pliable enough to be adapted not only to different cultures and countries but also to broad, systemic trends. This section discusses expected future trends in education and technology and then how a multidimensional, multi-tiered systems of support model for SA/A could be adapted. For brevity purposes, we group these trends into two broad categories: competency-based education and virtual learning (Kearney, 2016).

Competency-based education refers generally to mastery of academic and related material based on key benchmarks, and at a variable pace and timeline, rather than a strict focus on formal in-seat class time, examination scores, and credit accrual (Colby, 2017). Many schools in different countries have moved, or are moving toward, more holistic models of education that emphasize comprehension, innovation, conceptual connections, and critical thinking skills rather than simple recall and procedural steps (Jukes & Schaaf, 2019). In these authentic or ubiquitous learning environments, students are more apt to engage in project-, portfolio-, experiential-, and service-based activities to solve real-world problems, conduct experiments, interpret findings and literature, and make recommendations and presentations rather than simply taking multiple-choice tests, for example (Virtanen, Haavisto, Liikanen, & Kääriäinen, 2018). Many such environments also emphasize personalized, customized learning and curricula, including core social and behavioral competencies, for preparing individualized adult and career readiness plans (Ekstrand, 2015; Taylor, Oberle, Durlak, & Weissberg, 2017).

Virtual learning generally refers to online programming to deliver academic coursework and content (Brinson, 2015). Virtual learning environments are increasingly common at high school and postsecondary levels of education, but all future learning environments are expected to have at least some virtual component over the next several decades (Miron & Gulosino, 2016). Virtual learning environments can range in scope from adjunctive to hybrid to immersive in nature. An adjunctive scope may involve the introduction of greater technology into traditional classroom settings (e.g., game-based student-teacher interactions via tablets or smartphones; a hybrid or blended scope may combine online learning with direct (in-person) instructor contact; an immersive scope may involve a wholly digital network rather than a physical space that includes students from many different locations (Boelens, De Wever, & Voet, 2017; Hainey, Connolly, Boyle, Wilson, & Razak, 2016; Xie, Chu, Hwang, & Wang, 2019). Virtual learning environments, particularly immersive ones, can also vary with respect to time of individual and group work and perhaps be modified more quickly via learning analytics than traditional classrooms (Williamson, 2017).

Future trends in education and technology have serious ramifications for contemporary SA/A models. Researchers' traditional focus on outcomes such as percentage time missed from school as well as on concepts such as truancy or reluctance to attend school will need to be reconfigured in light of increasingly decentralized approaches to learning. In related fashion, researchers and others will likely need to reconsider traditional grade-level systems and academic calendars as schools increasingly modify the pace at which individual students learn, accrue credits (if relevant), and graduate.

A multidimensional multi-tiered system of supports model may be adaptable to these changes in education and technology. Indeed, various Tier 3 approaches for students largely disconnected or disengaged from school often focus on virtual, hybrid, project-based, and credit recovery and personalized learning approaches to provide alternative or blended pathways to adult and career readiness. In addition, many dimensional constructs associated with SA/A can dovetail with more dimensional aspects of the educational experience, including those linked to competencies, progression, completion, skill, and readiness for career paths. Finally, the model posed in this review is atheoretical, independent of academic timeline, and dexterous and malleable enough to accommodate rapid growth and immediate level change. Perhaps most importantly, the model emphasizes the promotion of school attendance and education in some form, an ever-present goal for all in this field.

Conclusion

School attendance and school absenteeism remain important avenues of focus for many different professionals across education, mental health, public policy, and myriad other areas. As noted in Part 1 of this two-part review, though meant to be comprehensive, this article focused on the primary methods of differentiating school attendance problems. Many nuanced distinctions based on multilevel and other statistical modeling should be noted, and many special circumstances such as intense school violence, extreme poverty, and geopolitical factors likely override the distinctions mentioned here. However, the main goal was to provide a heuristic model to help spur the field toward reconciliation, common language, and advancement while considering important aspects of prevention and intervention, particularly within schools.

Also as noted in Part 1 of this two-part review, we offer deep appreciation to all those who have dedicated their time and careers to helping youth succeed in school and move to a

more productive and healthy adulthood. The frameworks presented in this review are designed as looking glasses both into the past and future of SA/A and thus represent only a snapshot of the present state of affairs in this rapidly changing field. We look forward to learning about new and innovative developments in this field and hope that the ideas posed here offer some assistance.

CHAPTER 3

STUDY 2

Family environment variables as predictors of school absenteeism severity at multiple levels: Ensemble and classification and regression tree analysis

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Keywords: Absenteeism severity$_1$; truancy$_2$; ensemble analysis$_3$; classification and regression tree analysis$_4$; family environment$_5$; risk variables$_6$.

Abstract

School attendance problems, including school absenteeism, are common to many students worldwide, and frameworks to better understand these heterogeneous students include multiple classes or tiers of intertwined risk factors as well as interventions. Recent studies have thus examined risk factors at varying levels of absenteeism severity to demarcate distinctions among these tiers. Prior studies in this regard have focused more on demographic and academic variables and less on family environment risk factors that are endemic to this population. The present study utilized ensemble and classification and regression tree analysis to identify potential family environment risk factors among youth (i.e., children and adolescents) at different levels of school absenteeism severity (i.e., 1+%, 3+%, 5+%, 10+%). Higher levels of absenteeism were also examined on an exploratory basis. Participants included 341 youth aged 5-17 years (*M* = 12.2; *SD* = 3.3) and their families from an outpatient therapy clinic (68.3%) and community (31.7%) setting, the latter from a family court and truancy diversion program cohort. Family environment risk factors tended to be more circumscribed and informative at higher

levels of absenteeism, with greater diversity at lower levels. Higher levels of absenteeism appear more closely related to lower achievement orientation, active-recreational orientation, cohesion, and expressiveness, though several nuanced results were found as well. Absenteeism severity levels of 10-15% may be associated more with qualitative changes in family functioning. These data may support a Tier 2-Tier 3 distinction in this regard and may indicate the need for specific family-based intervention goals at higher levels of absenteeism severity.

Introduction

School attendance problems, including school absenteeism, are common to many students worldwide (UNESCO, 2012). School absenteeism has been linked to academic performance and achievement deficiencies, various mental health and social problems, and later school dropout (Attwood & Croll, 2015; Bridgeland, Dilulio, & Morison, 2006; Burton, Marshal, & Chisolm, 2014). School attendance problems leading to dropout can have lingering effects into adulthood as well, including increased risk for eventual economic, marital, occupational, and psychiatric problems (Christenson & Thurlow, 2004; Mazerolle et al., 2018; Rocque, Jennings, Piquero, Ozkan, & Farrington, 2017).

Recent theoretical frameworks of school attendance problems have focused on multiple classes or tiers of intertwined risk factors as well as interventions to fully capture the complexity of this heterogeneous population (Ingul, Havik, & Heyne, 2019; Kearney & Graczyk, 2014; Kearney, 2008; Skedgell & Kearney, 2018). Researchers have identified general classes of factors, such as child, parent, family, peer, school, and community variables, that enhance risk for school attendance problems (Burrus, & Roberts, 2012; Havik, Bru, & Ertesvåg, 2015; Ingul, Klöckner, Silverman, & Nordahl, 2012; Maxwell, 2016; McKee & Caldarella, 2016; Ready, 2010). These classes of risk factors often work in tandem, particularly with respect to chronic and severe school attendance problems and school dropout (Freeman & Simonsen, 2015).

Family environment type may be one such risk factor that directly impacts school attendance and academic achievement in youth (Epstein & Sheldon, 2002; Hill & Taylor, 2004). Bernstein and colleagues (1990; 1996; 1999), for example, identified several family variables associated with anxiety-based school refusal. These variables included lack of agreement among family members with respect to roles, inconsistency of family rules, and greater communication difficulties, rigidity, and disengagement. Lagana (2004) found that low family cohesion was more characteristic of students at medium to high risk of school dropout than those at low risk. Family structure and culture relate closely to school dropout as well (De Witte, Cabus, Thyssen, Groot, & van Den Brink, 2013).

Kearney and Silverman (1995) identified various dynamic subtypes among families of youth with broader school refusal behavior: enmeshed, detached, isolated, conflictive, healthy, and mixed. Enmeshed families display extreme closeness, emotional dependency, over-involvement, and loyalty but lack developmentally appropriate autonomy, leading some youth to feel insecure and display internalizing and externalizing symptoms (Barber & Buehler, 2006; Berryhill, Hayes, & Lloyd, 2018; Davies, Cummings, & Winter, 2004). Detached family members are relatively uninvolved or inattentive to one another, leading some youth to display internalizing and externalizing symptoms, poor emotional regulation, and insecure relationships with family members (Davies et al., 2004; Lindblom, Peltola, et al., 2017; Weiss & Cain, 1964).

Conflictive families display a lack of intimacy and emotional expression in addition to high rates of struggle and hostility among family members, leading some youth to display internalizing symptoms and risk-taking behaviors (Bradley et al., 2010; Chen, Wu, & Wei, 2017;

Jaycox & Repetti, 1993; Makihara, Nagaya, & Nakajima, 1985). Isolated families are characterized by minimal, if any, contact with people outside of the family, leading some youth to experience stress and social withdrawal (Tucker & Rodriguez, 2014; Wahler, 1980). Healthy families are characterized by adaptive functioning and good communication and problem-solving skills. Mixed families display characteristics of several of these patterns (Barber & Buehler, 2006; Kearney & Silverman, 1995).

In addition, researchers have begun to focus on the concept of multi-tiered systems of support (MTSS) and related models to conceptualize different layers of intervention for school attendance problems (Elliott & Place, 2019; Freeman et al., 2016; Kearney, 2016). MTSS aims to provide high-quality, individualized instruction and intervention, informed by frequent progress monitoring, for all aspects of student education (McIntosh & Goodman, 2016). MTSS models are often arranged in 3 tiers that focus on prevention (Tier 1), early intervention for emerging, acute problems (Tier 2), and intensive intervention for chronic and severe problems (Tier 3; Eagle, Dowd-Eagle, Snyder, & Holtzman, 2015). MTSS models have been applied to academic, social, and behavioral problems and skills across various age ranges and school settings (August, Piehler, & Miller, 2018).

Kearney and Graczyk (2014) were the first to apply MTSS principles to a model of school absenteeism directly. Each MTSS tier has a specific focus based on the severity of school absenteeism: (1) Tier 1 focuses on enhancing functioning and schoolwide attendance and preventing absenteeism for all students, (2) Tier 2 focuses on addressing students with emerging, acute, or mild to moderate school absenteeism, and (3) Tier 3 focuses on addressing students with chronic and severe school absenteeism (Kearney, 2016). Specific interventions are matched to each tier to help school personnel identify individualized responses. Recent research has demonstrated the value of applying MTSS models to school absenteeism. For example, schools that implement MTSS with higher fidelity have lower levels of school absenteeism than schools with less fidelity (Freeman et al., 2016). School districts may also include attendance measures in MTSS models (Coffey et al., 2018).

A key task for researchers utilizing MTSS models for school absenteeism has been to identify demarcations between the tiers. A distinction between Tiers 1 and 2 essentially means a distinction between nonproblematic and problematic behavior, such as between appropriate school attendance and school absenteeism in need of intervention (Pullen & Kennedy, 2019). However, no consistent, consensus definition for problematic school absenteeism exists across research disciplines or school districts (Gentle-Genitty, Karikari, Chen, Wilka, & Kim, 2015; Spruyt, Keppens, Kemper, & Bradt, 2016). Greater consensus can be found with respect to distinguishing Tiers 2 and 3, or identifying at what point school absenteeism is chronic and severe (DePaoli, Fox, Ingram, Maushard, Bridgeland, & Balfanz, 2015). Researchers, school districts, and other agencies sometimes utilize a 10% absenteeism cutoff to identify chronic absenteeism, though this is somewhat arbitrary and not universal (Conry & Richards, 2018).

Specific data-based demarcations between these tiers remain sparse, despite the fact that such distinctions would help inform early warning systems and intervention assignments for student absenteeism (Chu, Guarino, Mele, O'Connell, & Coto, 2018). Skedgell and Kearney (2016; 2018) found that risk factors for levels of absenteeism at 10% or higher tended to be more restricted than risk factors at lower levels of absenteeism. These studies focused primarily on academic and demographic variables, however, without examining family factors that have been identified as a key correlate of school attendance problems (Dahl, 2016).

The present study aimed to identify potential family environment risk factors among youth at different levels of school absenteeism severity (i.e., 1+%, 3+%, 5+%, 10+%). Participants included students referred for services due to substantial school absenteeism, which allowed for analysis of varying levels of severity. In accordance with recent calls to employ machine learning-based methods to examine risk factors for school absenteeism (Chung & Lee, 2019; Sansone, 2019), two sets of statistical approaches were utilized. Ensemble analysis, including chi-square adjusted interaction detection (CHAID), support vector machines, and neural network analyses, is a nonparametric method that combines multiple algorithmic models or classifiers to produce a single best model for a given data set (Berk, 2006). In addition, classification and regression tree analysis (CART) is a nonparametric method that identifies comprehensive subgroups based on interactions among multiple risk or predictor variables (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003). Nonparametric methods are increasingly used for academic variables denoted by categorical levels (e.g., Cordero, Santín, & Simancas, 2017; Lahti, Evans, Goodman, Schmidt, & LeCroy, 2019). Various levels of school absenteeism were examined, with a general expectation that risk factors at higher levels of absenteeism would be more restricted than risk factors at lower levels of absenteeism.

Materials and Methods

Participants

Participants included 341 youth (i.e., children and adolescents) aged 5-17 years (M = 12.2; SD = 3.3) and their families from an outpatient therapy clinic (68.3%) and community (31.7%) setting, the latter from a family court and truancy diversion program cohort. For the clinic sample, age range was 5-16 years (M = 11.0; SD = 3.2). Participants were primarily male (62.9%) and were European-American (78.2%), Asian (11.6%), Hispanic (5.8%), African

American (2.2%), multiracial or biracial (1.3%), and other (0.4%). For the community sample, age range was 11-17 years (*M* = 14.8; *SD* = 1.5). Participants were primarily female (53.7%) and were Hispanic (75.0%), African American (10.2%), other (5.6%), multiracial or biracial (3.7%), Asian (2.8%), and European-American (2.8%). Across both groups, most parents were married (50.0%); others were divorced (17.1%), separated (16.7%), never married (15.2%), or had another status (1.0%). Most fathers (57.0%) and mothers (63.3%) had graduated high school. Participants missed an average of 19.0% days of school (*SD* = 17.2) at time of assessment. Some youths were referred for treatment for school refusal behaviors (e.g., distress at school, morning misbehaviors designed to miss school, skipped classes, tardiness) that did not include formal full-day absences.

Measures

The Family Environment Scale: Form R (FES; Moos & Moos, 2009) is a 90-item true/false measure of current family relationships, personal growth, and family system maintenance. The FES comprises 10 subscales based on standard scores (mean, 50): cohesion (family member support of one another; COH), expressiveness (encouraging expression of feelings; EXP), conflict (open anger and hostility; CON), independence (self-sufficient, assertive members; IND), achievement orientation (activities cast in a competitive framework; ACH), intellectual-cultural orientation (family interest in intellectual and cultural issues; ICO), active-recreational orientation (participation in recreational/social activities; ARO), moral-religious emphasis (emphasis on ethical and religious values; MRE), organization (clear structure in activities; ORG), and control (set rules and procedures to structure family life; CTL). Internal consistency (Cronbach's alpha) ranges between 0.61-0.78. Cronbach's alpha for the items in the present study was 0.72. Two- and 4- month test-retest reliabilities range between 0.70-0.91

(Moos, 1990). FES item and subscale standard scores (*M* = 50.0) were utilized as the primary unit of analysis in the present study.

School staff or parents provided absenteeism severity data in the form of number of full school days missed. Percentage of full school days missed was calculated by dividing a student's total number of full school days missed by the number of days of school in that academic year, at the time of assessment, and then multiplying that number by 100.

Procedure and data analyses

Participants were recruited from a specialized outpatient therapy clinic or community setting. Participants in the community setting were referred to family court or a truancy diversion program by their school or parent(s)/guardian(s) based on prior school absences. Measures that included the FES were administered to youth and their parent(s)/guardian(s) independently and in the presence of a research assistant. Spanish versions of the measures were available. Study procedures, including parent consent and child assent, were approved by a university institutional review board.

Ensemble analysis was utilized to identify potential family environment risk factors among youth with school attendance problems across different levels of school absenteeism. Ensemble analysis is the combination of multiple algorithmic models or classifiers to produce one, best model that can be applied to the data (Berk, 2006). These models have been shown to outperform standard parametric methods, primarily due to the automation of identifying interactions and non-linearities and reducing overestimations of a model's predictive ability (Rosellini, Dussaillant, Zubizarreta, Kessler, & Rose, 2018). Ensemble analysis can include many different statistical methods; the present study utilized chi-square adjusted interaction detection (CHAID) decision trees, support vector machines, and neural network analyses.

Predictors were examined collectively and independently. A multiple imputation method was utilized; different plausible imputed data sets were examined, and combined results were obtained and reported here. Confusion matrices supported the use of CHAID decision trees as the best approach. In addition, CART analyses were utilized to more specifically examine clusters of FES items associated with enhanced risk for a particular level of absenteeism severity (i.e., 1+%, 3+%, 5+%, 10+%). Other absenteeism levels were examined on an exploratory basis (i.e., 15+%, 20+%, 30+%, 40+%). For brevity, significant results are reported.

Results

Absenteeism: 1+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 1+% absenteeism from youth with <1% absenteeism correctly identified 99.4% of participants and identified two main risk factors: FES items 1 and 44. Youth with items 1 (members help and support one another; COH) and 44 (little privacy in our family; IND) endorsed as true were at higher risk for 1+% absenteeism (66.5%); youth with items 1 and 44 endorsed as false were at lower risk (27.6%). The tree-model demonstrated higher sensitivity than specificity. Independent analysis of the predictors revealed that ARO scores significantly predicted 1+% absenteeism ($p < .02$, $F = 9.58$). ARO scores of <=53.0 indicated higher risk for 1+% absenteeism (80.1%); ARO scores of >53.0 indicated lower risk (19.9%). IND scores also significantly predicted 1+% absenteeism ($p < .05$, $F = 7.39$). IND scores of >37.0 indicated higher risk for 1+% absenteeism (67.7%); IND scores of <=37.0 indicated lower risk (32.3%).

CART item analysis identified three subgroups at highest risk for 1+% absenteeism (each node at 100.0%): (1) items 28 (true; talk about religious meaning; MRE) and 40 (true; set ways of doing things; CTL); (2) items 28 (true; talk about religious meaning; MRE), 39 (true; on time is very important; ORG), 40 (false; set ways of doing things; CTL), and 62 (true; money/bills openly talked about; EXP); and (3) items 28 (false; talk about religious meaning; MRE), 29 (true; hard to find things; ORG), and 44 (true; very little privacy in family; IND). The tree-model's accuracy in predicting 1+% absenteeism was approximately 91.3%.

Absenteeism: 3+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 3+% absenteeism from youth with <3% absenteeism correctly identified 83.2% of participants and identified several items (2, 25, 31, 42, 62, 89) and subscale scores as risk factors (Table 6). The tree-model demonstrated higher sensitivity than specificity. The final node representing highest overall risk of 3+% absenteeism (.968) included items 2 (true; members keep feelings to self; EXP), 25 (true), and 42 (true; doing things spur of the moment; EXP). Independent analysis of the predictors revealed that ARO scores significantly predicted 3+% absenteeism ($p < .01$, $F = 12.62$). ARO scores of <=53.0 indicated higher risk for 3+% absenteeism (80.1%); ARO scores of >53.0 indicated lower risk (19.9%).

Table 6

FES Subscale Standard Scores Predictive of 3+% Absenteeism

	Higher risk	Lower risk
Expressiveness	34.0-51.5 (8.6%)	59.0-60.0 (3.2%)
Achievement orientation	>47.0 (4.3%)	<=47.0 (4.2%)
Moral-religious emphasis	<=61.0 (5.0%)	>61.0 (2.7%)
Independence	<=37.0 (2.4%)	>37.0 (2.3%)

Note: Subscales presented in descending order of impact.

CART item analysis identified four subgroups at highest risk for 3+% absenteeism (each node at 100.0%): (1) items 25 (true; money not very important to us; ACH) and 31 (true; feeling of family togetherness; COH); (2) items 25 (false; money not very important to us; ACH), 31 (false; feeling of family togetherness; COH), and 89 (true; dishes done immediately after eating; ORG); (3) items 2 (true; members keep feelings to self; EXP), 5 (true; important to be best; ACO), 25 (true; money not very important to us; ACH), and 53 (false; members sometimes hit; CON); and (4) items 2 (false; members keep feelings to self; EXP), 14 (false; encouraged to be independent; IND), 25 (true; money not very important to us; ACH), 86 (true; like art and music; ICO), and 90 (false; can't get away with much; CTL). The tree-model's accuracy in predicting 3+% absenteeism was approximately 85.7%.

Absenteeism: 5+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 5+% absenteeism from youth with <5% absenteeism correctly identified 76.3% of participants and identified several items (2, 29, 35, 40, 50, 62, 71) and subscale scores as risk factors (Table 7). The tree-model demonstrated higher sensitivity than specificity. The final node representing highest overall risk of 5+% absenteeism (.986) included items 2 and 29 (true) and IND scores of <=37. Independent analysis of the predictors revealed that ARO scores significantly predicted 5+% absenteeism ($p < .02$, $F = 9.57$, predicted .760). ARO scores of <=53.0 indicated higher risk for 3+% absenteeism (80.1%); ARO scores of >53.0 indicated lower risk (19.9%).

Table 7

FES Subscale Standard Scores Predictive of 5+% Absenteeism

	Higher risk	Lower risk
Expressiveness	40.8-51.5 (10.0%)	59.0-60.0 (3.7%)
Cohesion	>32.7 (10.2%)	<=32.7 (3.1%)
Independence	>37.0 (4.9%)	<=37.0 (3.0%)
Moral-religious emphasis	<=61.0 (3.5%)	>61.0 (2.3%)
Conflict	>43.0 (7.8%)	<=43.0 (2.2%)

Note: Subscales presented in descending order of impact.

CART item analysis identified three subgroups at highest risk for 5+% absenteeism (each node at 100.0%): (1) items 51 (true; members back each other; COH), 56 (false; someone plays a musical instrument; ICO), and 77 (true; members go out a lot; ARO); (2) items 34 (false; we come and go as we want; IND), 45 (true; strive to do things better; ACO), 74 (true; hard to be by self without hurting feelings; IND), and 77 (false; members go out a lot; ARO); and (3) items 16 (true; rarely go to plays/concerts; ICO), 17 (false; friends often come over; ARO), 29 (false; hard to find things; ORG), 74 (false; hard to be by self without hurting feelings; IND), and 77 (false; members go out a lot; ARO). The tree-model's accuracy in predicting 5+% absenteeism was approximately 74.5%.

Absenteeism: 10+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 10+% absenteeism from youth with <10% absenteeism correctly identified 58.3% of participants and identified several items (4, 11, 16, 17, 44, 49, 68, 79, 87) and subscale scores as risk factors (Table 8). The tree-model demonstrated higher sensitivity than specificity. The final node representing highest overall risk of 10+% absenteeism (1.000) included ORG scores of 53.0-58.0, ICO scores of 35.9-41.0, and item 17 (true; friends come over; ARO). Independent analysis of the predictors revealed that COH scores significantly predicted 10+% of days missed. COH scores of <=52.0 indicated higher risk of 10+% absenteeism (54.8%); COH scores of >52.0 indicated lower risk (45.2%). CART item analysis identified one main subgroup at elevated risk for 10+% absenteeism (node at 87.5% probability): (1) items 74 (true; hard to be by self without hurting feelings; IND) and 77 (false; members go out a lot; ARO). The tree-model's accuracy in predicting 10+% absenteeism was approximately 78.3%.

Table 8

FES Subscale Standard Scores Predictive of 10+% Absenteeism

	Higher risk	Lower risk
Organization	53.0-58.0 (23.4%)	48.0-53.0 (2.5%)
Moral-religious emphasis	<=61.0 (5.2%)	61.0-65.9 (2.1%)
Expressiveness	>51.5 (7.3%)	46.8-51.5 (2.1%)
Intellectual-cultural orientation	47.0-58.0 (6.2%)	<35.9 (3.1%)
Achievement orientation	>53.0 (3.7%)	46.8-51.5 (2.6%)
Conflict	<=44.0 (2.2%)	>44.0 (2.1%)

Note: Subscales presented in descending order of impact.

Absenteeism: Higher levels

CHAID analyses were also conducted on an exploratory basis for absenteeism levels of 15+%, 20+%, 30+%, and 40+%. The final collective tree-model that best differentiated youth with 15+% absenteeism from youth with <15% absenteeism correctly identified 52.9% of participants and identified several items (14, 28, 42, 61, 71, 75) and subscale scores as risk factors. The tree-model demonstrated higher specificity than sensitivity. MRE scores of >61.0 indicated higher risk of 15+% absenteeism (17.0%); MRE scores of <= 43.9 indicated lower risk (10.9%). ACH scores of <=47 indicated higher risk of 15+% absenteeism (16.6%); ACH scores of >59.0 indicated lower risk (5.4%). CTL scores of >47.2 indicated higher risk of 15+% absenteeism (6.2%); CTL scores of 42.9-47.2 indicated lower risk (2.3%). IND scores of 51-53 indicated higher risk of 15+% absenteeism (4.7%); IND scores of >53.0 indicated lower risk (2.6%). ARO scores of <=48.0 indicated higher risk of 15+% absenteeism (3.3%); ARO scores of >48.0 indicated lower risk (2.6%). The final node representing highest overall risk of 15+% absenteeism (.867) included MRE scores of 56.0-61.0, item 42 (true; doing things spur of the moment; EXP), and item 75 (true; work before play is the rule; ICO). Independent analysis of predictors revealed that ACH scores significantly predicted 15+% of days missed ($p < .04$, $F = 8.16$, predicted = 0.47). ACH scores of <=47.0 indicated higher risk of 15+% absenteeism (52.2%); ACH scores of >47.0 indicated lower risk (47.8%).

The final collective tree-model that best differentiated youth with 20+% absenteeism from youth with <20% absenteeism correctly identified 61.4% of participants and identified several items (4, 49, 79) and subscale scores as risk factors. The tree-model demonstrated higher specificity than sensitivity. COH scores of 23.0-45.9 indicated higher risk of 20+% absenteeism (27.9%); COH scores of >65.0 indicated lower risk (9.8%). CTL scores of 23.0-45.9 indicated higher risk of 20+% absenteeism (27.9%); CTL scores of >65.0 indicated lower risk (9.8%). EXP scores of 34.0-47.0 indicated higher risk of 20+% absenteeism (10.0%); EXP scores of <= 34.0 indicated lower risk (4.9%). MRE scores of >61 indicated higher risk of 20+% absenteeism (5.1%); MRE scores of 43.9-51.0 indicated lower risk (2.4%).

The final collective tree-model that best differentiated youth with 30+% absenteeism from youth with <30% absenteeism correctly identified 75.0% of participants and identified several items (18, 20, 30, 43, 85) and subscale scores as risk factors. The tree-model demonstrated higher specificity than sensitivity. COH scores of 23.0-45.9 indicated higher risk of 30+% absenteeism (27.9%); COH scores of 52-52.6 indicated lower risk (6.5%). MRE scores of 36.0-46.0 indicated higher risk of 30+% absenteeism (4.0%); MRE scores of <=36 indicated lower risk (3.1%). EXP scores of 34.0-47.0 indicated higher risk of 30+% absenteeism (10.0%); EXP scores of <= 34.0 indicated lower risk (4.9%). IND scores of >37.0 indicated higher risk of 30+% absenteeism (7.2%); IND scores of <= 37.0 indicated lower risk (4.2%). CTL scores of <=43.0 indicated higher risk of 30+% absenteeism (3.9%); CTL scores of >53.3 indicated lower risk (3.7%). CON scores of 44.0-54.3 indicated higher risk of 30+% absenteeism (6.9%); CON scores of 38.5-43.0 indicated lower risk (2.4%). Independent analysis of the predictors revealed that ACH scores significantly predicted 30+% of days missed ($p < .05$, $F = 7.87$). ACH scores of <=51.0 indicated higher risk of 30+% absenteeism (52.5%); ACH scores of >51.0 indicated lower risk (47.5%).

The final collective tree-model that best differentiated youth with 40+% absenteeism from youth with <40% absenteeism correctly identified 85.0% of participants and identified several items (10, 49, 55) and subscale scores as risk factors. The tree-model demonstrated higher specificity than sensitivity. COH scores of 23.0-45.9 indicated higher risk of 40+%

absenteeism (10.2%); COH scores of 52.6-59 indicated lower risk (3.2%). MRE scores of 46.0-61.0 indicated higher risk of 40+% absenteeism (38.8%); MRE scores of <=36 indicated lower risk (7.5%). ORG scores of <=53.0 indicated higher risk of 40+% absenteeism (16.2%); ORG scores of >53.0 indicated lower risk (6.6%). IND scores of <=51 indicated higher risk of 40+% absenteeism (5.2%); IND scores of >51.0 indicated lower risk (5.0%). ARO scores of <=61.0 indicated higher risk of 40+% absenteeism (5.4%); ARO scores of >61.0 indicated lower risk (25.0%).

Discussion

The present study examined family environment variables as potential predictors of various absenteeism severity levels. The findings reveal that several family environment variables are indeed related to different severity levels in both broad and more nuanced ways. Broadly, as expected, family environment risk factors tended to be more circumscribed and informative at higher levels of absenteeism, with much greater diversity at lower levels. Higher levels of absenteeism (i.e., 15+%) appear more closely related to lower achievement orientation, active-recreational orientation, cohesion, and expressiveness. Lower levels of absenteeism (i.e., 1%, 3%, 5%) were generally associated with a wider array of family environment variables.

Active-recreational standard scores were generally suppressed across absenteeism severity levels, a result that parallels Hansen and colleagues' (1998) finding that less active families were associated with greater levels of school absenteeism among youth with anxiety-based conditions. These authors speculated that a low emphasis on social and physical activities and greater time spent at home may mean that some children may be more apt to spend school time at home. In addition, these children may be more predisposed to have difficulties with social skills and peer interactions that could also interfere with school attendance. Some have also found that school absenteeism is related to less participation in school sports (Hunt & Hopko, 2009), though others have not (Skedgell & Kearney, 2018). Lower active-recreational scores were evident as well in Kearney and Silverman's (1995) study that led those authors to conclude that some families of youth with absentee problems are isolated in nature.

A number of nuanced findings were also revealed in the present study, however, that deserve detailed description. With respect to achievement orientation, for example, elevated standard scores were associated with less absenteeism severity but lower standard scores were associated with greater absenteeism severity. Higher school performance is generally associated with higher competition (Harrison & Rouse, 2014), though effects can depend on gender and age (Little & Garber, 2004; Wang & Holcombe, 2010). At the family level, achievement orientation could translate into specific activities such as modeling academic advancement, reading frequently, encouraging a strong work ethic, and providing enrichment opportunities that distally affect school attendance (Dubow, Boxer, & Huesmann, 2009).

In addition, lower standard scores for expressiveness were evident at less severe (3%, 5%) and more severe (20%, 30%) levels of absenteeism, though elevated standard scores were predictive of 10+% absenteeism. As noted earlier, Bernstein and Borchardt (1996) found that families of youth with school refusal displayed significant problems with respect to role performance and communication. Findings from the present study indicate that such difficulties may be less evident during periods when families are working together to solve an absentee problem and during periods when frustration over long-term absenteeism has led to greater disengagement and less opportunities for direct expression (Kearney & Silverman, 1995).

Family cohesion represented another nuanced finding. Cohesion was not predictive at 1+% and 3+% absenteeism but lower standard scores were more predictive of higher levels of absenteeism. This result parallels Bernstein and colleagues' (1999) finding that adolescents with school attendance problems and their parents viewed their families as particularly rigid and disengaged on a cohesion dimension. In addition, several researchers have found, broadly speaking, that parent and family involvement and support are crucial variables with respect to school attendance, performance, and dropout (Parr & Bonitz, 2015; Sheldon, 2007; Topor, Keane, Shelton, & Calkins, 2010). Cohesion in the form of help with homework, support for academic progress, and commitment to education may be key in this regard (Wilder, 2014).

Family conflict was expected to be an important predictor of absenteeism severity in the present study. Elevated conflict standard scores were more predictive of 5+% absenteeism severity, whereas lower conflict standard scores were more predictive of 10+% absenteeism severity. Some have found family conflict to be elevated in this population in general, and advocate for the problem to be resolved clinically in this population (Kearney & Albano, 2018; Kearney & Silverman, 1995), though others have found family conflict to be unrelated to school attendance problems (McShane, Walter, & Rey, 2001). As with expressiveness, some families may display increased conflict at a point of urgency when trying to resolve a school attendance problem but later become frustrated and disengaged from the process (Kearney, 2019).

Finally, control was a family environment variable that did not appear until higher levels of absenteeism severity. Lower levels of control were more predictive at higher levels of absenteeism severity, particularly at the 20+% and 30+% levels. A less structured home environment has been associated with school absenteeism in other studies (Hunt & Hopko, 2009). In addition, as mentioned earlier, Bernstein and colleagues (1990) found that inconsistency of family rules related to some youth with school attendance problems.

Conversely, family rules are part of a parent involvement process often associated with academic success (Catsambis, 2001).

Analyses of individual FES items also revealed interesting findings. First, items were sometimes endorsed differently in different nodes, indicating a high level of variability in these groups. This applied particularly to lower levels of absenteeism. Second, fewer items were predictive of 10+% absenteeism than at lower levels, mirroring the subscale finding that predictors tended to be more restricted at higher absenteeism severity levels. Overall, however, examining subscale scores appeared to be more useful than examining item scores.

The present study may thus have some applicability to MTSS models of school absenteeism and how tiers within these models may be demarcated. In particular, absenteeism severity levels of 10-15% appear to be associated with more defined sets of risk factors, which may indicate more qualitative changes in family functioning at these levels. More intense drops in achievement orientation, active-recreational orientation, cohesion, and expressiveness, in addition to less conflict, may indicate that families become substantially more disengaged at these levels. Such disengagement could come in the form of sharply reduced parent-school official contact, consequences for school absenteeism, academic assistance, attendance monitoring, and parent supervision (Kearney & Albano, 2018).

The results may also have implications for MTSS development in educational settings. Many local educational agencies, for example, are moving toward systemic, evidence-based systems of academic and behavioral supports to meet the unique needs of diverse students (McIntosh & Goodman, 2016). A better understanding of how these needs intersect with family-based challenges is essential in this respect. Parental involvement, for example, has been found to be a key element of success in MTSS programs, and such programs often benefit from a wider array of stakeholders that include parents (August, Piehler, & Miller, 2018). In addition, MTSS models are increasingly moving toward a "whole child" approach that more fully considers ecological levels outside of school, such as family factors (Sailor, McCart, & Choi, 2018). Results of the present study and related studies may thus help inform such an approach.

Results of the present study also have implications for further research work in this area, particularly with respect to how these findings intersect with other family-based risk factors for school absenteeism. Gubbels and colleagues (2019), for example, conducted a meta-analytic review of such factors for school absenteeism and dropout and found several pertinent family domains. These included low parental school involvement, lack of nuclear family structure, and low parental control, among others. An understanding of how the family environment dynamics identified in the present study intersect with these broader domains, particularly with respect to specific levels of school absenteeism, would be quite instructive for subtyping and demarcation purposes. Such information may also help inform family-based treatment for this population. For example, Tobias (2019) found that family-based intervention for persistent school absenteeism was often hindered by an insecure home environment. The latter construct could be investigated in greater detail in future work to identify whether the dynamics noted in the present study would apply.

Limitations of the present study should be noted. First, the sample was a diverse one ranging from having no formal school absences to having many school absences. Second, more detailed analyses of absenteeism type or of demographic or developmental differences were not examined in accordance with sample constraints and diversity of settings. Third, the primary dependent measure was based on parent-report. Future researchers should endeavor to explore a more wide-ranging assessment of family functioning in this population.

Conclusion

Despite these limitations, findings from the present study may have some clinical implications. Educators, mental health professionals, and others who address these families, particularly at higher levels of absenteeism severity, will likely need to prioritize certain goals given the problematic family dynamics involved. With respect to school attendance, such goals may include repairing parent-school official communications, educating family members about creative educational options, and establishing contracts or agreements to improve problem-solving ability and increase incentives for attending school (Kearney, 2019). More broadly, such goals may include interventions to enhance family engagement and communication as well as contacts with outside sources of support (Kelly, Rossen, & Cowan, 2018).

CHAPTER 4

STUDY 3

Internalizing symptoms as predictors of school absenteeism severity at multiple levels: Ensemble and classification and regression tree analysis

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Abstract

School attendance problems are highly prevalent worldwide, leading researchers to investigate many different risk factors for this population. Of considerable controversy is how internalizing behavior problems might help to distinguish different types of youth with school attendance problems. In addition, efforts are ongoing to identify the point at which children and adolescents move from appropriate school attendance to problematic school absenteeism. The present study utilized ensemble and classification and regression tree analysis to identify potential internalizing behavior risk factors among youth at different levels of school absenteeism severity (i.e., 1+%, 3+%, 5+%, 10+%). Higher levels of absenteeism were also examined on an exploratory basis. Participants included 160 youth aged 6-19 years (M = 13.7; SD = 2.9) and their families from an outpatient therapy clinic (39.4%) and community (60.6%) setting, the latter from a family court and truancy diversion program cohort. One particular item relating to lack of enjoyment was most predictive of absenteeism severity at different levels, though not among the highest levels. Other internalizing items were also predictive of various

levels of absenteeism severity, but only in a negatively endorsed fashion. Internalizing symptoms of worry and fatigue tended to be endorsed higher across less severe and more severe absenteeism severity levels. A general expectation that predictors would tend to be more homogeneous at higher than lower levels of absenteeism severity was not generally supported. The results help confirm the difficulty of conceptualizing this population based on forms of behavior but may support the need for early warning sign screening for youth at risk for school attendance problems.

Introduction

School attendance problems are a worldwide phenomenon linked to a plethora of academic, social, and physical and mental health problems in children and adolescents (Kearney, Gonzálvez, Graczyk, & Fornander, 2019a, b). Factors that elevate risk of school attendance problems are myriad as well and are often grouped into child-, parent-, family-, peer-, school-, and community-based variables (e.g., Havik, Bru, & Ertesvåg, 2015). Child-based risk factors of school attendance problems include extensive work hours outside of school, grade retention, office disciplinary referrals, low school commitment and engagement, poor health or academic proficiency, problematic interpersonal relationships, substance use, and underdeveloped social and academic skills, among others (Ekstrand, 2015; Gubbels, van der Put, & Assink, 2019; Kearney, 2008). Other child-based risk factors of school attendance and academic achievement problems, as well as later school dropout, have involved various psychopathological conditions and symptoms (Kearney, 2016; Macklem, 2014; Parr & Bonitz, 2015).

School attendance problems have been linked historically to a variety of internalizing and externalizing behavior problems and disorders, most notably anxiety and mood disorders and disruptive behavior disorders (Jones, West, & Suveg, 2019; Kearney & Albano, 2004).

Internalizing problems common to this population include general, social, and separation anxiety as well as worry, fear, depression, somatic complaints, fatigue, social withdrawal, sleep disturbance, and self-consciousness (Egger, Angold, & Costello, 2003; Gonzalvez et al., 2019; Maynard et al., 2015). Externalizing problems common to this population include noncompliance, defiance, verbal and physical aggression, temper tantrums, refusal to move, running away from school or home, and antisocial and disruptive behavior at school and elsewhere (Ingul, Klöckner, Silverman, & Nordahl, 2012; Kearney, 2019). In addition, internalizing and externalizing problems are highly comorbid within and across each set in this population (Finning et al., 2019; Hankin et al., 2016).

In recent years, researchers have endeavored to move toward more detailed, nuanced, and sophisticated profiles of psychopathology in youth with school attendance problems, particularly with respect to internalizing behaviors and their treatment (Crawley et al., 2014; Ek & Eriksson, 2013; Fiorilli, De Stasio, Di Chiacchio, Pepe, & Salmela-Aro, 2017; Maynard et al., 2018). For example, researchers have found that depression and less prosocial behaviors are often primary features of anxious youth with school attendance problems (Pflug & Schneider; 2016; Sibeoni et al., 2018; Tekin, Erden, Ayva, & Büyüköksüz, 2018). In addition, others have associated school attendance problems linked with internalizing behaviors to key profiles surrounding optimism/pessimism, positive/negative affect, social functioning, and anxiety severity (Fernández-Sogorb, Inglés, Sanmartín, Gonzálvez, & Vicent, 2018; Gonzálvez et al., 2016, 2019; Sanmartín et al., 2018).

Researchers have also endeavored to link specific psychopathological symptoms to various levels of school absenteeism severity. For example, Lawrence and colleagues (2019) found that students with a mental disorder displayed less school attendance than students without a mental disorder, missing 11.8 school days in years 1-6, 23.1 days in years 7-10, and 25.8 days in years 11-12. In addition, for those students with a mental disorder, absences due to a particular disorder accounted for 13.4% of all days absent from school (rising to 16.6% in years 11-12). Skedgell and Kearney (2016) also examined internalizing symptoms among youth with 0-14% and 15-100% absenteeism severity, finding the latter group (and particularly those at 20-39%) to display significantly more general and separation anxiety and depression. Stempel and colleagues (2017) similarly compared youth who had missed less than versus more than 15 days of school, finding that more chronic absenteeism was associated with more adverse childhood experiences such as financial hardship, divorce, parental incarceration, domestic or neighborhood violence, and family mental disorder or substance use.

A link between specific psychopathological symptoms and other risk factors with various levels of school absenteeism severity has important potential implications beyond basic research and classification. Certainly such a link can inform medical and mental health professionals who address youth with school attendance problems, and assessment and intervention protocols can be variously adapted to cases of mild/moderate versus chronic/severe absenteeism (Heyne et al., 2002; Kearney & Albano, 2018). Many school-based professionals and districts also distinguish between students with less severe and more severe academic and behavioral problems as they work to optimize limited intervention resources (August, Piehler, & Miller, 2018; McIntosh, Bohanon, & Goodman, 2010). Indeed, many schools have been forced to take on the role of mental health care and have thus sought out ways to screen for various mental health problems (Merikangas et al., 2011; Stiffler & Dever, 2015). Suggestions for what mental health symptoms relate to various levels of absenteeism severity would, for example, be helpful in this regard (Dowdy et al., 2015).

The need for more informed mental health screening in schools dovetails nicely with recent theoretical frameworks of school attendance problems that focus in part on multi-tiered interventions. Many school districts have adopted multi-tiered systems of support (MTSS) models for prevention and intervention of mental health concerns (Splett et al., 2018). MTSS models typically focus on prevention (Tier 1), early intervention for emerging, acute, or mild to moderate problems (Tier 2), and intensive intervention for chronic and severe problems (Tier 3) (Eagle, Dowd-Eagle, Snyder, & Holtzman, 2015). MTSS models can apply to a wide variety of academic, social, and behavioral problems, including those with internalizing behavior problems (Weist et al., 2018).

Kearney and Graczyk (2014; Kearney, 2016) were the first to apply MTSS principles to school attendance problems. In this model, Tier 1 strategies focus on enhancing functioning and schoolwide attendance and on preventing school attendance problems for all students, Tier 2 strategies focus on students with emerging, acute, or mild to moderate school attendance problems, often to reintegrate them to school, and Tier 3 strategies focus on students with chronic and severe school attendance problems, often to provide alternative pathways to graduation. Specific interventions may be matched to each tier based on absenteeism severity and degree of risk and contextual factors to help school personnel and others identify individualized responses (Elliott & Place, 2019; Freeman et al., 2016; Kearney, 2016).

As mentioned, MTSS models are increasingly adapted to a wide variety of academic, social, and behavioral problems, including now school attendance problems. A particular challenge for advocates of these models, however, has been to demarcate tiers within the system. A distinction between Tier 1 and Tier 2, for example, indicates a distinction between less problematic and more problematic behavior such as school absenteeism (Pullen & Kennedy, 2019). Unfortunately, no consensus distinction currently exists in this regard (Chu, Guarino, Mele, O'Connell, & Coto, 2018; Lyon & Cotler, 2007; Spruyt, Keppens, Kemper, & Bradt, 2016). In addition, distinctions between Tier 2 and Tier 3 remain variable. School attendance problems are sometimes considered to be chronic and severe (Tier 3) at a 10% threshold (DePaoli, Fox, Ingram, Maushard, Bridgeland, & Balfanz, 2015). Skedgell and Kearney (2016; 2018) found that risk factors for higher severity levels of absenteeism tended to be more homogeneous than risk factors at lower levels of absenteeism. However, data to support a Tier 2-Tier 3 distinction remain needed (Conry & Richards, 2018).

The present study aimed to identify potential internalizing symptom risk factors among youth at different levels of school absenteeism severity (i.e., 1+%, 3+%, 5+%, 10+%). Such differentiations might help inform distinctions between tiers in an MTSS model of school absenteeism. In accordance with recent calls to employ machine learning-based methods to examine risk factors for school absenteeism (Chung & Lee, 2019; Sansone, 2019), two sets of statistical approaches were utilized. Ensemble analysis, including chi-square adjusted interaction detection (CHAID), support vector machines, and neural network analyses, is a nonparametric method that combines multiple algorithmic models or classifiers to produce a single best model for a given data set (Berk, 2006). In addition, classification and regression tree analysis (CART) is a nonparametric method that identifies comprehensive subgroups based on interactions among multiple risk factors or predictor variables (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003). These analyses are aimed to generate and not test hypotheses (Markham et al., 2013). Various levels of school absenteeism were examined, with a general expectation that risk factors at higher levels of absenteeism would be more homogeneous than risk factors at lower levels of absenteeism.

Materials and Methods

Participants

Participants included 160 youth aged 6-19 years (M = 13.7; SD = 2.9) and their families from an outpatient therapy clinic (39.4%) and community (60.6%) setting in southern Nevada, the latter from a family court and truancy diversion program cohort. The clinic cohort involved students referred to therapy services for absenteeism; the community cohort involved students given a truancy citation by school police for absenteeism and referred to an 8-week diversion program. Participants were primarily male (51.2%) and diverse with respect to ethnicity: Hispanic (51.0%), European-American (26.1%), Asian (8.9%), African American (6.4%), multiracial or biracial (4.5%), and other (2.5%). Most parents were married (44.6%); others were divorced (22.3%), separated (18.5%), never married (12.7%), or had another status (1.9%). Most fathers (48.0%) and mothers (59.9%) graduated high school. Participants missed a mean of 19.0% days of school (SD = 16.9) at time of assessment. Some youths were referred for treatment for school refusal behaviors (e.g., distress at school, morning misbehaviors designed to miss school, skipped classes, tardiness) that did not include formal absences.

Measures

The Revised Children's Anxiety and Depression Scale (RCADS; Chorpita et al., 2000) is a 47-item self-report or parent-report measure of child internalizing behavior disorders with the following subscales and number of items: separation anxiety (7), social phobia (9), generalized anxiety(6), obsessive-compulsive(6), panic disorder (9), and major depression (10). Items are scored on a Likert-type 0-3 scale of agreement (never = 0, sometimes = 1, often = 2, always = 3). Internal consistency is good for each subscale, with Cronbach's alpha between 0.78-0.88 (Chorpita, Moffitt, & Gray, 2005). Cronbach's alpha for RCADS items in the present study was

0.86. Confirmatory factor analysis indicated the 6-factor model is an adequate fit, with loadings from 0.51-0.79 (Chorpita et al., 2005).

School staff or parents provided absenteeism severity data in the form of number of full school days missed. Percentage of full school days missed was calculated by dividing the student's total number of full school days missed by the number of days of school in that academic year, at the time of assessment, and then multiplying that number by 100. Assessments were conducted at different points throughout the academic year.

Procedure and data analyses

Participants were recruited from a specialized outpatient therapy clinic or community setting. Participants in the community setting were referred to family court or a truancy diversion program by their school or parent(s)/guardian(s) based on prior school absences. Following parent consent and child assent, measures that included the RCADS were administered to youth and their parent(s)/guardian(s) independently and in the presence of a research assistant. Spanish versions of the measures were available.

Ensemble analysis was utilized to identify potential family environment risk factors among youth with school attendance problems across different levels of school absenteeism. Ensemble analysis is the combination of multiple algorithmic models or classifiers to produce one, best model that can be applied to the data (Berk, 2006). These models have been shown to outperform standard parametric methods, primarily due to the automation of identifying interactions and non-linearities and the reduction of overestimations of a model's predictive ability (Rosellini, Dussaillant, Zubizarreta, Kessler, & Rose, 2018). Ensemble analysis can include many different statistical methods; the present study utilized chi-square adjusted interaction detection (CHAID) decision trees, support vector machines, and neural network analyses. Predictors were examined collectively and independently. A multiple imputation method was utilized; different plausible imputed data sets were examined and combined results were obtained and reported here. Confusion matrices supported the use of CHAID decision trees. In addition, CART analyses were utilized to more specifically examine clusters of RCADS items associated with enhanced risk for a particular level of absenteeism severity (i.e., 1+%, 3+%, 5+%, 10+%). Other absenteeism levels were examined on an exploratory basis (i.e., 15+%, 20+%, 30+%, 40+%), as was latent class analysis for 0-10% and 10+% absenteeism. For brevity, significant results are reported. No gender differences were found with respect to RCADS Anxiety and Depression T-scores.

Results

Absenteeism: 1+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 1+% absenteeism from youth with <1% absenteeism correctly identified 99.6% of participants and identified one main risk factor: item 6 (nothing fun anymore; DEP). Item 6 scores of >0.0 indicated higher risk of 1+% absenteeism (69.3%); item 6 scores of 0.0 indicated lower risk (30.7%). The tree-model demonstrated higher sensitivity than specificity. Independent analysis revealed no significant predictors. CART item analysis similarly identified one subgroup at highest risk for 1+% absenteeism (node at 100.0%): endorsement of sometimes, often, or always on item 6 and endorsement of never on item 46 (scared if away from home overnight; SEP). The overall tree-model's accuracy in predicting 1+% absenteeism was approximately 95.7%.

Absenteeism: 3+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 3+% absenteeism from youth with <3% absenteeism correctly identified 83.7% of participants and identified one main risk factor: item 6 (nothing fun anymore; DEP). Item 6 scores of >0.0 indicated higher risk of 3+% absenteeism (53.4%); item 6 scores of 0.0 indicated lower risk (46.6%). The tree-model demonstrated higher sensitivity than specificity. Independent analysis of the predictors revealed that item 6 ($p < 0.01$, $F = 12.19$) and item 35 scores ($p < 0.01$, $F = 7.81$) significantly predicted 3+% absenteeism. With respect to item 35 (worry about what will happen; GAD), scores of 0.0 indicated higher risk (59.0%); scores of >0.0 indicated lower risk (41.0%). CART item analysis identified one main subgroup at highest risk for 3+% absenteeism (node at 100.0%): endorsement of sometimes, often, or always on items 6 (nothing fun anymore; DEP) and 38 (afraid to talk in front of class; SOP) as well as endorsement of never or sometimes on item 46 (scared if away from home overnight; SEP). The overall tree-model's accuracy in predicting 3+% absenteeism was approximately 92.1%.

Absenteeism: 5+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 5+% absenteeism from youth with <5% absenteeism correctly identified 76.7% of participants and identified one main risk factor: item 6 (nothing fun anymore; DEP). Item 6 scores of >0.0 indicated higher risk of 5+% absenteeism (53.4%); item 6 scores of 0.0 indicated lower risk (46.6%). The tree-model demonstrated higher sensitivity than specificity. Independent analysis of the predictors revealed that item 6 ($p < 0.01$, $F = 12.19$), 35 ($p < 0.05$, $F = 6.30$) and 38 scores ($p < 0.05$, $F = 6.81$) significantly predicted 5+% absenteeism. With respect to item 35 (worry about what will happen; GAD), scores of 0.0 indicated higher risk

(59.0%); scores of >0.0 indicated lower risk (41.0%). With respect to item 38 (afraid to talk in front of class; SOP), scores of 0.0 indicated higher risk (61.3%); scores of >0.0 indicated lower risk (38.7%).

CART item analysis identified one main subgroup at highest risk for 5+% absenteeism (node at 100.0%): endorsement of never on item 17 (scared to sleep on own; SEP) and often or always on item 24 (with a problem, heart beats fast; PAN). The overall tree-model's accuracy in predicting 5+% absenteeism was approximately 84.9%. Latent class analysis of <10% absenteeism revealed a primary cluster that contained 41% of cases. In this cluster, RCADS items 1-4, 7, 12, 13, 21, 25, and 30 (3 DEP, 2 GAD, 2 SOP, 1 PAN) were primarily endorsed as sometimes; all other items in this cluster were endorsed as never.

Absenteeism: 10+%

For the CHAID analysis, the final collective tree-model that best differentiated youth with 10+% absenteeism from youth with <10% absenteeism correctly identified 58.5% of participants and identified one main risk factor: item 6 (nothing fun anymore; DEP). Item 6 scores of >0.0 indicated higher risk of 1+% absenteeism (52.3%); item 6 scores of 0.0 indicated lower risk (47.7%). The tree-model demonstrated higher sensitivity than specificity. Independent analysis of the predictors revealed that obsession/compulsions T-scores significantly predicted 10% of days missed ($p < 0.01$, $F = 12.38$). Obsession/compulsions T-scores of <=48.0 indicated higher risk of 10+% absenteeism (57.8%); obsession/compulsions T-scores of >48.0 indicated lower risk (42.2%). In addition, endorsement of never on several items was also predictive of 10+% absenteeism: items 8 (worried when someone angry at me; SOP; 65.3%/34.7%), 9 (worry about being away from parents; SEP; 68.4%/31.6%), 29 (feel worthless; DEP; 66.7%/33.3%), 30 (worry about making mistakes; SOP; 67.6%/32.4%), 42 (have to do things over and over; OCD; 61.5%/38.5%), and 44 (have to do things in just the right way; 54.9%/46.1%).

CART item analysis identified one main subgroup at highest risk for 10+% absenteeism (node at 85.6%): endorsement of never on item 17 (scared to sleep on own; SEP). The overall tree-model's accuracy in predicting 10+% absenteeism was approximately 84.2%. Latent class analysis of 10+% absenteeism revealed a primary cluster that contained 34% of cases. In this cluster, RCADS items 1, 4, 8, 21, and 30 (3 SOP, 1 DEP, 1 GAD) were primarily endorsed as sometimes; all other items in this cluster were endorsed as never.

Absenteeism: Higher levels

CHAID analyses were also conducted on an exploratory basis for absenteeism levels of 15+%, 20+%, 30+%, and 40+%. The final collective tree-model that best differentiated youth with 15+% absenteeism from youth with <15% absenteeism correctly identified 52.9% of participants and identified one main risk factor: item 6 (nothing fun anymore; DEP). Item 6 scores of >0.0 indicated higher risk of 15+% absenteeism (52.3%); item 6 scores of 0.0 indicated lower risk (47.7%). The tree-model demonstrated higher specificity than sensitivity. Independent analysis revealed no subscale scores to be significant predictors of 15+% absenteeism. In addition, endorsement of never on several items was also predictive of 15+% absenteeism: items 1 (worry about things; GAD; 60.9%/39.1%), 8 (worried when someone angry at me; SOP; 65.3%/34.7%), 9 (worry about being away from parents; SEP; 68.4%/31.5%), 25 (cannot think clearly; DEP; 66.9%/33.1%), and 29 (feel worthless; DEP; 66.7%/33.3%).

The final collective tree-model that best differentiated youth with 20+% absenteeism from youth with <20% absenteeism correctly identified 61.4% of participants and identified one main risk factor: item 6 (nothing fun anymore; DEP). Item 6 scores of >0.0 indicated higher risk of 1+% absenteeism (52.3%); item 6 scores of 0.0 indicated lower risk (47.7%). The tree-model demonstrated higher specificity than sensitivity. Independent analysis of the predictors revealed that item 42 significantly predicted 20+% absenteeism ($p < 0.05$, $F = 6.58$). Item 42 (have to do things over and over; OCD) scores of 0.0 indicated higher risk for 20+% absenteeism (61.5%); item 42 scores of >0.0 indicated lower risk (38.5%).

The final collective tree-model that best differentiated youth with 30+% absenteeism from youth with <30% absenteeism correctly identified 75.3% of participants and identified two main risk factors: item 8 (worried when someone angry at me; SOP) and separation anxiety subscale scores. Item 8 scores of >0.0 indicated higher risk of 30+% absenteeism (64.9%); item 8 scores of 0.0 indicated lower risk (35.1%). Separation anxiety T-scores of <=61.0 indicated higher risk of 30+% absenteeism (53.1%); separation anxiety T-scores of >61.0 indicated lower risk (46.9%). The tree-model demonstrated higher specificity than sensitivity.

The final collective tree-model that best differentiated youth with 40+% absenteeism from youth with <40% absenteeism correctly identified 83.9% of participants and identified one main risk factor: item 28 (with a problem, feel shaky; PAN). Item 28 scores of 0.0 indicated higher risk of 40+% absenteeism (50.6%); item 28 scores of >0.0 indicated lower risk (49.4%). The tree-model demonstrated higher specificity than sensitivity.

Discussion

The present study examined internalizing behaviors as potential predictors of various absenteeism severity levels. The findings revealed that one particular depression item (nothing much fun anymore) helped most to demarcate different severity levels, up to a point. In addition, a number of other internalizing items were predictive of various levels of absenteeism severity, but only in a negatively endorsed fashion. Overall, internalizing items that tended to be endorsed higher across less severe and more severe absenteeism severity levels included those relating to worry and fatigue. A general expectation that predictors would tend to be more homogeneous at higher than lower levels of absenteeism severity was not generally supported.

One particular item was found to consistently distinguish lower and higher levels of absenteeism severity at different benchmarks: item 6 (nothing is much fun anymore), which is an item on the RCADS depression subscale. Two general possibilities may exist for this finding. First, school attendance problems are indeed commonly associated with symptoms of depression, one of the rare consistent findings over several decades with respect to internalizing psychopathology in this population (Egger et al., 2003; Gallé-Tessonneau, Johnsen, & Keppens, 2019; Kearney, 1993). Depression is also commonly associated or comorbid with anxiety disorders in this population, making attempts at diagnostic classification difficult (Jones & Suveg, 2015). Antidepressant medication is recommended for many adolescents with school attendance problems, and cognitive-behavioral therapies for this population often focus on depression symptoms (Londono Tobon, Reed, Taylor, & Bloch, 2018; Maynard, Brendel, Bulanda, Heyne, Thompson, & Pigott, 2015; Melvin & Gordon, 2019).

Finning and colleagues (2019), in their meta-analysis of depression and school attendance problems, concluded that symptoms of depression are indeed common to many different types of school attendance problems. The authors also postulated several possible mechanisms for this association, such as social withdrawal, sleep disturbance, and low energy. Youth with school refusal behavior do tend to have social functioning problems and withdraw from friends and other peers at school (Gonzálvez et al., 2019; Havik, Bru, & Ertesvåg, 2015). Others indeed show difficulties with sleep (including going to bed very late), energy, and physical activity (Ek & Eriksson, 2013; Hochadel, Frölich, Wiater, Lehmkuhl, & Fricke-Oerkermann, 2014; Mannino et al., 2019). However, each set of behaviors - social and sleep problems and school attendance problems - may precede the other in different cases (Kearney, 2019).

Second, the depression item noted above may also indicate a relative amount of boredom, frustration, burnout, or lack of self-efficacy with respect to the school environment or academic performance (Fiorilli et al., 2017; Reid, 2012). Finning and colleagues (2019) noted that another mechanism explaining depression and school attendance problems might be loss of motivation. Surveys of youth with school attendance problems or who have dropped out of school regularly reveal boredom with classes and the school environment as a key reason for leaving (Attwood & Croll, 2015; Kearney, 2016; Strand, 2014). Others have noted as well that youth with learning disorders can become frustrated and eventually miss school (Redmond & Hosp, 2008). Poor school climate or school-based curricula perceived as tedious or inflexible by students are associated with school attendance problems as well (Hendron & Kearney, 2016; Maxwell, 2016; Wang, & Degol, 2016). Interestingly, the finding regarding item 6 disappeared at particularly high levels of absenteeism severity (i.e., 30+% and 40+%), possibly suggesting that some youth discovered outside-of-school avenues to boost enjoyment (Kearney & Albano, 2018).

A key finding of the present study was that lack of endorsement of several anxiety items was what most predicted higher absenteeism severity levels. The findings also indicated substantial variability with respect to individual items. One possibility is that higher absenteeism severity levels are associated more with externalizing than internalizing symptoms (Maynard, Salas-Wright, Vaughn, & Peters, 2012). In addition, youth in the present study were examined at different points of the academic year, but anxiety levels may be more pronounced at the beginning of a year (Ingul & Nordahl, 2013). Higher levels of absenteeism severity also mean more time out of school and thus relief from school-based anxiety symptoms (Skedgell & Kearney, 2018). Other variables such as family or school environment may thus be better predictors of absenteeism severity (Fornander & Kearney, 2019).

The lack of endorsement and variability shown in the present study may also help confirm that reliance on various forms of specific behavior to identify classes of school attendance problems is quite difficult (Inglés, Gonzálvez , Garcia-Fernandez, Vicent, & Martínez-Monteagudo, 2015). Kearney (2002) advocated for the term negative affectivity rather than specific symptoms of anxiety or depression among youth with school attendance problems to account for the vagaries of internalizing symptoms characteristic of this population. Indeed, historically, many researchers have focused on broad descriptors of emotional distress (e.g., dread, upset, misery) to describe youth who are reluctant to attend school (Kearney, 2001). Perhaps not surprisingly, the items that tended to be elevated more in the current study were those related to broader concepts such as worry and fatigue. Others have found considerable heterogeneity within and across classes of behavior among children with school attendance problems, and Kearney (2007) found that functions of school refusal behavior were superior to forms of behavior in predicting absenteeism severity.

Limitations of the present study should be noted. First, the sample was an eclectic one that ranged from having no formal school absences to having many school absences. Second, sample size constraints did not permit more nuanced analyses of absenteeism type, setting, or demographic or developmental differences, though studies generally indicate emotional distress across many absence types in this population (Finning, Ford, Moore, & Ukoumunne, 2019). Third, the primary dependent measure was based on self-report, though these kinds of measures are commonly used for youth with internalizing symptoms (Chorpita et al., 2000). In related fashion, broader measures such as diagnostic interviews, behavioral observations, and parent and teacher reports were not used and may have provided more sophisticated information about participants' internalizing symptoms.

Conclusion

Despite these limitations, the present study may have some applicability to MTSS models of school absenteeism and how tiers within these models may be demarcated. Psychosocial screenings for anxiety and depression at early warning sign stages for problematic absenteeism may be advisable, and may help distinguish Tier 1 school attendance from emerging Tier 2 school attendance problems (Ingul, Havik, & Heyne, 2019). Findings from the present study may further support the need for preventative practices in this population as well, particularly for targeted practices aimed toward those with depressive symptoms (Werner-Seidler, Perry, Calear, Newby, & Christensen, 2017).

CHAPTER 5

DISCUSSION

The current study aimed to support a precise definition of problematic school absenteeism, inform the MTSS approach, and identify specific subgroups of youth at various levels of risk for displaying problematic school absenteeism based upon family environment and youth psychopathology. The identification of a precise definition of problematic school absenteeism is crucial to identify the severity of the problem accurately and to increase the clarity and utility of early assessment and intervention methods for youth with problematic school absenteeism, particularly methods that utilize the MTSS framework. Similarly, the identification of high-risk subgroups, provides school-based personnel with specific guidelines for the interpretation of early absenteeism and family environment screening data, thereby allowing students to be categorized efficiently into one of the MTSS tiers for intervention. The current study extends the literature in multiple ways. First, study one extends the literature by providing a review of the extensive school absenteeism literature focusing specifically on differentiating school attendance problems and providing a heuristic model that includes common language and advances the field. Second, study two adds to the relatively small literature base linking the family environment to problematic school absenteeism and provides family-based mental health providers with profiles of families at high risk of having a youth with problematic school absenteeism. Third, study three extends the available literature base linking youth psychopathology to problematic school absenteeism and provides school-based personnel with specific guidelines for the interpretation of early absenteeism and youth mental health screening data, thereby allowing students to efficiently be categorized into one of the MTSS tiers for intervention. Fourth, studies two and three extend the literature by utilizing nonparametric ensemble analysis to produce one model of problematic school absenteeism that has been applied to the data in many different ways.

Clinical implications

The current study has potential clinical and school implications. The primary goal of study one was to provide a heuristic model to encourage the field to focus on common language and advancement with an important consideration for prevention and intervention, particularly interventions within the school setting. The multidimensional multi-tiered system of supports model proposed by study one is beneficial for clinicians and educators as it is (1) adaptable to advances in education and technology, (2) able to merge with dimensional aspects of education such as competency, progression, completion, skill, and readiness benchmarks, (3) atheoretical, (4) independent of an academic timeline, and (5) able to accommodate rapid growth and change. Study two has clinical implications for educators and clinicians as they work with students with problematic absenteeism and complicated family dynamics that are often involved. The current study supports goals focused on repairing parent-school official communications, educating family members about creative educational options, and establishing contracts or agreements to improve problem-solving ability and increase incentives for attending school. Findings also support interventions aimed at enhancing family engagement, communication, and interaction with outside sources of support. Study three has clinical implications for clinicians and educators working with students with problematic school absenteeism. The current study may help to demarcate the tiers within the MTSS model and provide more specific guidelines for educators and clinicians. Findings support psychosocial screenings for anxiety and depression at early warning stages to differentiate between tier 1 and tier 2 attendance problems and to ensure early intervention for at-risk students. The current study also supported the need for preventative practices specifically aimed at students with depressive symptoms (Werner-Seidler et al., 2017).

Limitations

Limitations of the current study should be noted. Study one aimed to review the past and potential future of the school absenteeism literature but is only a snapshot of the current state of this rapidly evolving field. Further, the distinctions made in study one are likely superseded by a multitude of exceptional circumstances, including intense school violence, extreme poverty, and geopolitical factors. Study two and study three share specific limitations. First, the sample was diverse and included students with a wide range of school absences. Second, sample size constraints did not allow for further evaluation of absenteeism type, setting, demographic, or developmental differences. Specific to study two, the primary dependent measure was based on parent-report. On the other hand, the primary dependent measure in study three was based on self-report. Finally, study three did not utilize diagnostic interviews, behavioral observations, and parent and teacher reports that may have provided more insight into student internalizing symptoms.

Recommendations for future research

Future research is warranted to extend the findings of the current study and address identified limitations. Research should continue to study appropriate definitions of problematic school absenteeism and the MTSS tiers to further support a unified definition within the field. The role of future changes in education and technology and the potential impacts on school absenteeism behavior and presentation should be investigated. The findings of study two could be extended by including other family-based risk factors for school absenteeism. A better understanding of how family environment dynamics intersect with broader domains would be beneficial for subtyping and further differentiating the MTSS tiers. The role of an insecure home environment should be further investigated to identify whether the dynamics in the current study would apply. Future research should consider including a more wide-range assessment of family functioning among students with problematic school absenteeism. The findings of study two could be extended by evaluating the role of externalizing difficulties in higher absenteeism severity levels. Given that study three did not support the assumption that predictors would be more homogenous at higher, rather than lower, levels of absenteeism, future research should explore whether there are specific factors that do increase the homogeneity of the high-risk groups. Finally, there are a multitude of additional risk factors that should be assessed utilizing reports from various sources (e.g., parent, self, teacher) and settings (e.g., home, school, community).

APPENDIX A

CCSD IRB Approval

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

May 12, 2017

Mirae Fornander
University of Nevada, Las Vegas
4505 S. Maryland Parkway
Las Vegas, NV 89154

Dear Mirae:

The Research Review Committee of the Clark County School District has reviewed your requested amendment to your request entitled: *School Refusal Behavior: Las Vegas Truancy Diversion Program & Application #35 (formerly # RRC-17-2015).* The committee is pleased to inform you that your proposal has been approved with the following provisos:

1. Participation is strictly and solely on a voluntary basis.
2. Provide letter of acceptance from any additional principals who agree to be involved with the study.
3. The project is approved to take place at Desert Pines High School.

This research protocol is approved for a period of one year from the approval date. The expiration of this protocol is 8/15/2018. If the use of human subjects described in the referenced protocol will continue beyond the expiration date, you must provide a letter requesting an extension *one month* prior to the date of expiration. 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 to 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

APPENDIX B

UNLV IRB Approval

UNLV

UNLV Social/Behavioral IRB - Expedited Review
Modification Approved

DATE:	November 20, 2018
TO:	Christopher Kearney, Ph.D.
FROM:	UNLV Social/Behavioral IRB
PROTOCOL TITLE:	[710884-11] School Refusal Behavior: The Effectiveness of a Las Vegas Truancy Diversion Program
SUBMISSION TYPE:	Amendment/Modification
ACTION:	APPROVED
APPROVAL DATE:	November 20, 2018
EXPIRATION DATE:	April 4, 2019
REVIEW TYPE:	Expedited Review

Thank you for submission of Amendment/Modification materials for this protocol. The UNLV Social/Behavioral IRB has APPROVED your submission. This approval is based on an appropriate risk/benefit ratio and a protocol design wherein the risks have been minimized. All research must be conducted in accordance with this approved submission.

Modifications reviewed for this action include:

1. Addition of Roy W. Martin Middle School and John C. Fremont Professional Development Middle School and Robert E. Lake Elementary School as research sites.
2. Addition of the following research team members: Melanie Rede, Shadie Burke, Mallory Contantine, Allyssa Howell, Anthony Romero, Brittany Klenczar, Brittany Miller, Carolyn Osborne, Jordan Donohue, Katie Mayfield, Kayla Millette, Keiyan Silos, Leo Lyon, Lorena Beltran, Luis Torres, Pamela Green, Rebecca Smith, Steffi Del Rosario, Valerie Velasco and Jefferson Arcaina.

This IRB action will not reset your expiration date for this protocol. The current expiration date for this protocol is April 4, 2019.

PLEASE NOTE:
If your project has been revised and now involves paying research participants or the procedures for paying participants has been changed, it is recommended to contact Carisa Shaffer, ORI Program Coordinator at (702) 895-2794 to ensure compliance with subject payment policy.

Should there be *any* change to the protocol, it will be necessary to submit a **Modification Form** through ORI - Human Subjects. No changes may be made to the existing protocol until modifications have been approved.

ALL UNANTICIPATED PROBLEMS involving risk to subjects or others and SERIOUS and UNEXPECTED adverse events must be reported promptly to this office. Please use the appropriate reporting forms for this procedure. All FDA and sponsor reporting requirements should also be followed.

All NONCOMPLIANCE issues or COMPLAINTS regarding this protocol must be reported promptly to this office.

This protocol has been determined to be a Minimal Risk protocol. Based on the risks, this protocol requires continuing review by this committee on an annual basis. Submission of the **Continuing Review Request Form** must be received with sufficient time for review and continued approval before the expiration date of April 4, 2019.

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

UNLV Social/Behavioral IRB - Exempt Review
Exempt Notice

DATE:	June 14, 2018
TO:	Christopher Kearney, Ph.D.
FROM:	Office of Research Integrity - Human Subjects
PROTOCOL TITLE:	[1244800-1] Review of clinic data
ACTION:	DETERMINATION OF EXEMPT STATUS
EXEMPT DATE:	June 14, 2018
REVIEW CATEGORY:	Exemption category # 4

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 45CFR46.101(b) and deemed exempt.

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

PLEASE NOTE:
Upon final determination of exempt status, the research team is responsible for conducting the research as stated in the exempt application reviewed by the ORI - HS and/or the IRB which shall include using the most recently submitted Informed Consent/Assent Forms (Information Sheet) and recruitment materials.

If your project involves paying research participants, it is recommended to contact Carisa Shaffer, ORI Program Coordinator at (702) 895-2794 to ensure compliance with the Policy for Incentives for Human Research Subjects.

Any changes to the application may cause this protocol to require a different level of IRB review. Should any changes need to be made, please submit a **Modification Form**. When the above-referenced protocol has been completed, please submit a **Continuing Review/Progress Completion report** to notify ORI - HS of its closure.

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
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Bachelor of Arts August 2011-May 2015

Hastings College (Hastings, NE)
Bachelor of Arts in Psychology with a Political Science Minor

HONORS AND AWARDS

Lovinger Award	UNLV	2019 & 2018
Outstanding Graduate Student Teaching Award	UNLV	2019
Patricia Sastaunik Scholarship	UNLV	2017, 2018, & 2019
Outreach Undergraduate Mentoring Program (OUMP) Mentor Award	UNLV	2018
Summer Session Scholarship	UNLV	2017
Lorrie E. Bryant Psi Chi Award	Hastings College	2014

GRANTS AND FELLOWSHIPS

Open Article Fund Grant	UNLV	$1,500	July & July 2019

Grant funded the publishing of two manuscripts in open-access journals.

Summer Doctoral Research Fellowship	UNLV	$7,000	May 2019

Merit-based research fellowship for doctoral students who have demonstrated excellence in their field of study and provided summer support to decrease graduation time.

Regent Service Program Grant	UNLV	~$12,000	August 2018 & 2019

Grant funded two full-time undergraduate research assistants.

PUBLICATIONS

Peer Reviewed

1. **Fornander, M.J.**, & Kearney, C.A. (2020). Internalizing symptoms as predictors of school absenteeism severity at multiple levels: Ensemble and classification and regression tree analysis. *Frontiers in Psychology*, 10, 3079. https://doi.org/10.3389/fpsyg.2019.03079

2. **Fornander, M.J.**, & Kearney, C.A. (2019). Family environment variables as predictors of school absenteeism severity at multiple levels: Ensemble and classification and regression tree analysis. *Frontiers in Psychology*, 10, 1916. https://doi.org/10.3389/fpsyg.2019.02381

3. Kearney, C.A., Gonzalvez, C., Graczyk, P., & **Fornander, M.J.** (2019). Reconciling contemporary approaches to school attendance and school absenteeism: Toward promotion and nimble response, global policy review and implementation, and future adaptability (Part 1). *Frontiers in Psychology*, 10, 1916. https://doi.org/10.3389/ fpsyg.2019.02222

4. Kearney, C.A., Gonzalvez, C., Graczyk, P., & **Fornander, M.J.** (2019). Reconciling contemporary approaches to school attendance and school absenteeism: Toward promotion and nimble response, global policy review and implementation, and future adaptability (Part 2). *Frontiers in Psychology*, 10, 2605. https://doi.org/10.3389/fpsyg.2019.02605

5. 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. https://doi.org/10.1177/1534650116685619

Book Chapters

1. **Fornander, M.J.** (2020) Using YouTube in psychology. In W.Weiten. Psychology: Themes and Variations--Online Resources. Boston: Cengage.

2. Kearney, C.A., & **Fornander, M.J.** (2018). School refusal behavior and absenteeism. In R.J.R. Levesque (Ed.), Encyclopedia of adolescence (2nd ed.) (pp. 3298-3303). New York: Springer.

PUBLICATIONS IN PREPARATION:

1. **Fornander, M.J.**, Bates, C.R., Dreyer Gillette, M.L. (In preparation) The psychosocial predictors of treatment response in family-based weight management program.

2. Bates, C., Pallotto, I., **Fornander, M.J.**, & Dreyer Gillette, M. (In preparation). A mixed-methods examination of family rules, routines, and caregiver distress during the first year of pediatric cancer treatment.

ORAL PRESENTATIONS

International

1. Kearney, C.A., **Fornander, M.J.,** Howard, A., & Bacon, V. (2018, March). *The role of the School Refusal Assessment Scale in an evolving multi-tiered system of supports model*. Oral paper presented at the meeting of the Lorentz Center conference on School absenteeism: Universal problem seeks gold standard solutions, Leiden, Netherlands.

2. Kearney, C.A., **Fornander, M.J.,** Howard, A., & Bacon, V. (2018, March). *The short version of a long, troubled history of differentiating among school attendance problems*. Oral paper presented at the meeting of the Lorentz Center conference on School absenteeism: Universal problem seeks gold standard solutions, Leiden, Netherlands.

National

1. **Fornander, M.J.**, Bacon, V.R., Garcia, B., Sherwood, S., Rede, M., Kearney, C.A. (2019, October). *Guidelines for in-school exposures*. Oral presentation at the Selective Mutism Association (SMA) National Conference, Las Vegas, NV.

2. Diliberto, R., **Fornander, M.J.**, & Bacon, B. (2018, September). *Selective mutism basics: A crash course*. Oral presentation at the Selective Mutism Association (SMA) National Conference, Chicago, IL.

3. Kearney, C.A., **Fornander, M.J.,** & Howard, A.N. (2017, March). *Assessment and intervention for problematic school absenteeism*. Oral presentation at the School Social Work Association of America (SSWAA) Conference, San Diego, CA.

4. +Burke, M., Delgado, J., **Nakouzi, M.,** & Sharp, M. (2015, March). *Does type of activity impact the positive effect of nature on students' attention and mood?* Oral presentation at the Great Plains Students' Psychology Convention, Wichita, KS.
   +Great Plains Students' Psychology Convention, 1st place outstanding presentation award.

5. **Nakouzi, M.** (2014, April). *Factors that impact terrorist recruitment*. Oral presentation at Midwest Political Science Undergraduate Research Conference, Parkville, MO

Local

1. **Fornander, M.J.** (2018, April). *Identifying youth at risk for problematic school absenteeism using nonparametric modeling: The impact of youth psychopathology and family environment risk factors.* Oral presentation at the University of Nevada, Las Vegas Psychology Department Research Fair, Las Vegas, Nevada.

2. **Fornander, M.J.,** Sheldon, K.K., & Kearney, C. (2016, October). *School refusal*. Oral presentation at the Nevada Association of School Psychologists (NASP) Conference, Las Vegas, NV.

3. **Nakouzi, M.,** Wendland, M., Lee, R., Kemler, J., Gonzales-Hunter, T., & Easter, S. (2015, April) *Forging global alliances: Practicing diplomacy at National Model United Nations*. Oral presentation at Academic Showcase, Hastings, NE.

4. Burke, M., Delgado, J., **Nakouzi, M.,** & Sharp, M. (2015, April). *Does type of activity impact the positive effect of nature on students' attention and mood?* Oral presentation at Academic Showcase, Hastings, NE.

5. Burke, M., Delgado, J., **Nakouzi, M.,** & Sharp, M. (2014, April). *Does type of activity impact the positive effect of nature on students' attention and mood?* Oral presentation at Academic Showcase, Hastings, NE.

6. **Nakouzi, M.,** Wendland, M., Lee, R., Kemler, J., & Gonzales-Hunter, T. (2014, April) *Exploring world politics through the National Model United Nations*. Oral presentation at Academic Showcase, Hastings, NE.

POSTER PRESENTATIONS

National

1. Roberts, T., **Fornander, M.J.**, Egan, A.M., & Moser, C. (2021, April). *Gender dysphoria, general well-being, BMI, and weight-related behaviors among adolescent transgender males.* Poster submitted to the Pediatric Academic Societies Annual Conference (PAS), Virtual.

2. **Fornander, M.J.**, Egan, A.M., Roberts, T., & Moser, C. (2021, April). *BMI and associated variables in a pediatric gender clinic sample.* Poster submitted to the Pediatric Academic Societies Annual Conference (PAS), Virtual.

3. **Fornander, M.J.**, Bates, C.R., Dreyer Gillette, M.L. (2021, April). *Impact of COVID-19 on families with a child in cancer treatment.* Poster to be presented at the Society of Pediatric Psychology Annual Conference (SPPAC), Virtual.

4. **Fornander, M.J.**, Bacon, V.R., Rede, M., & Kearney, C.A. (2020, November). *Identifying protective factors for school absenteeism.* Poster presented at the Association for Behavioral and Cognitive Therapies (ABCT), Virtual.

5. Bacon, V.R., Rede, M., Warhola, Z., **Fornander, M.J.**, & Kearney, C.A. (2020, November). *Student perceptions of school staff's respect for diversity is related to bullying and feelings of safety.* Poster presented at the Association for Behavioral and Cognitive Therapies (ABCT), Virtual.

6. Bacon, V.R, **Fornander, M.J.**, Kearney, C.A. (2019, October). *Characteristics of communication behaviors in children with selective mutism.* Poster presented at the Selective Mutism Association (SMA) National Conference, Las Vegas, NV.

7. Howard, A.N., **Fornander, M.J.**, Bacon, V., Rede, M., Burke, S., Constantine, M., Gerthoffer, A., Diliberto, R., Kearney, C.A. (2019, October). *Somatic symptoms and internalizing problems as moderators of selective mutism severity*. Poster presented at the Selective Mutism Association (SMA) National Conference, Las Vegas, NV.

8. **Fornander, M.J.**, Bacon, V., Rede, M., Constantine, M., Burke, S., Howard, A., Gerthoffer, A., Diliberto, R., Kearney, C.A. (2019, October). *Selective mutism presentation in U.S. versus Non-US children.* Poster presented at the Selective Mutism Association (SMA) National Conference, Las Vegas, NV.

9. Bacon, V.R, **Fornander, M.J.**, Rede, M., Constantine, M., Burke, S., Howard, A., Gerthoffer, A., Kearney, C.A. (2019, May). *Bullying as a risk factor for school absenteeism.* Poster presented at the Association for Psychological Science (APS), Washington, D.C.

10. *Millette, K., Beltran, L., **Fornander, M.J.,** Bacon, V., Kearney, C.A., (2019, April). *Parent level of control & problematic school absenteeism.* Poster presented at the Western Psychological Association conference (WPA), Pasadena, CA.

11. *Silos, K., Bacon, V., **Fornander, M.J.,** Kearney, C.A. (2019, April). *Social anxiety and the functions of school refusal behavior.* Poster presented at the Western Psychological Association conference (WPA), Pasadena, CA.

12. **Fornander, M.J.**, Bacon, V., Howard, A., Gerthoffer, A., & Kearney, C.A. (2018, November). *Internalizing symptoms as predictors of problematic school absenteeism*. Poster presented at the annual meeting of the Association of Behavioral and Cognitive Therapies, Washington, DC.

13. **Fornander, M.J.**, Bacon, V., Howard, A., Gerthoffer, A., & Kearney, C.A. (2018, November). *Predicting school refusal behavior with youth report of school climate.* Poster presented at the annual meeting of the Association of Behavioral and Cognitive Therapies, Washington, DC.

14. Bacon, V., **Fornander, M.J.,** Howard, A., Gerthoffer, A., Kearney, C.A. (2018, September). *Boys will be boys? Gender differences in informant reports of symptoms in children with selective mutism.* Poster presented at the Selective Mutism Association (SMA) National Conference, Chicago, IL.

15. **Fornander, M.J.**, Bacon, V., Diliberto, R., Howard, A., Kearney, C.A. (2018, September). *Predicting symptoms severity in children with selective mutism.* Poster presented at the Selective Mutism Association (SMA) National Conference, Chicago, IL.

16. Howard, A.N., Velasco, V., **Fornander, M.J**., Gerthoffer, A., Bacon, V., & Kearney, C.A. (2018, August). *Re-experiencing symptoms in childhood PTSD act as a protective factor against dissociative symptoms.* Poster presented at the annual meeting of the American Psychological Association. San Francisco, CA.

17. *Velasco, V., Howard, A., **Fornander, M.J.,** Gerthoffer, A., Bacon, V., Kearney, C.A. (2018, April). *PTSD symptom clusters predict dissociative symptoms in maltreated youth.* Poster presented at the Western Psychological Association (WPA) Annual Conference, Portland, OR.

18. **Fornander, M.J.,** Howard, A.N., Gerthoffer, A., Skedgell, K.K., Bacon, V., & Kearney, C.A. (2017, November). *Youth spoken language and ethnic identity are associated with important protective factors against school refusal behavior.* Poster presented at the Association of Behavioral and Cognitive Therapies (ABCT) National Conference, San Diego, CA.

19. Sheldon, K.K., **Fornander, M.J.,** & Kearney, C.A. (2016, October). *Selective mutism group treatment.* Poster presented at the Selective Mutism Group (SMG) National Conference, Manhattan Beach, CA.

20. Sheldon, K.K., **Fornander, M.J.,** & Kearney, C.A. (2016, September). *ADHD symptoms in youth who are truant.* Poster presented at the Society for Police and Criminal Psychology (SPCP) National Conference, Austin, TX.

21. **Nakouzi, M.** & Droege, T. (2013, December). *Body image awareness week at Hastings College.* Poster presented at Active Minds National Conference, Washington D.C.

<u>Local</u>

1. **Fornander, M.J.**, Egan, A.M., Roberts, T., & Moser, C. (2021, April). *BMI and associated variables in a pediatric gender clinic sample.* Poster submitted to Children's Mercy Research Days Annual Conference, Virtual

2. **Fornander, M.J.**, Bates, C.R., Dreyer Gillette, M.L. (2021, April). *Impact of COVID-19 on families with a child in cancer treatment.* Poster submitted to Children's Mercy Research Days Annual Conference, Virtual

3. *Arcaina, V.J., **Fornander, M.J**., Kearney, C.A. (2019, October). *Presentation of internalizing symptoms in youth with selective mutism.* Poster presented at the Diversity Research and Mentorship Reception, Las Vegas, NV.

4. *Sweis, R., Kustura, M., Del Rosario S., Bacon, V.R., **Fornander, M.J**., Kearney, C.A. (2019, October). *Family factors in children with selective mutism.* Poster presented at the Diversity Research and Mentorship Reception, Las Vegas, NV.

5. ***Lyon, L.R., **Fornander, M.J.**, & Kearney, C.A. (2018, October). *Efficacy of exposure therapy on youth with selective mutism: Future approaches towards treatment.* Poster presented at McNair Scholars Symposium, Las Vegas, NV.

6. **Fornander, M.J.** & Kearney, C.A. (2019, February). *Defining problematic school absenteeism: Identifying youth at risk.* Poster presented at the Graduate & Professional Student Research Forum, Las Vegas, NV.

7. *Velasco, V., Howard, A., **Fornander, M.J.,** Gerthoffer, A., Bacon, V., Kearney, C.A. (2018, May). *PTSD symptom clusters predict dissociative symptoms in maltreated youth.* Poster presented at the Nevada Psychological Association (NPA) Annual Conference, Las Vegas, NV.

8. **Fornander, M.J**., Lozano, A., Perez, F., Rodriguez, A., Bacon, V., Howard, A., Gerthoffer, A., & Kearney, C.A. (2018, May). *School climate risk and protective factors of school refusal behavior*. Poster presented at the annual meeting of the Nevada Psychological Association, Las Vegas, NV.

9. **Fornander, M.J.,** Howard, A.N., Gerthoffer, A., Skedgell, K.K., Bacon, V., & Kearney, C.A. (2017, May). *Youth spoken language and ethnic identity are associated with important protective factors against school refusal behavior.* Poster presented at the Diversity Research & Mentorship Reception, Las Vegas, NV.

10. **Fornander, M.J.,** Howard, A.N., Gerthoffer, A., Skedgell, K.K., Bacon, V., & Kearney, C.A. (2017, May). *Youth spoken language and ethnic identity are associated with important protective factors against school refusal behavior.* Poster presented at the Nevada Psychological Association (NPA) Annual Conference, Las Vegas, NV.

Note: * indicate mentored students/trainees

RESEARCH MENTORSHIP

Undergraduate Honors Thesis Mentor & Committee Member	February 2019- November 2019
Undergraduate McNair Scholars Institute Student Mentor	March 2018-September 2019

RESEARCH EXPERIENCE

Division of Developmental and Behavioral Health
Children's Mercy Hospital

Supervisor: Elizabeth Willen, Ph.D.

Resident Researcher *October 2020-Present*

Participating in the Cardiac Neurodevelopmental Outcome Collaborative (CNOC): Diversity and Inclusion Special Interest Group (SIG) to promote diversity by developing best-practice standards for clinical care and research to enhance health equity in children with congenital heart defects. Duties will include collecting data, preparing datasets for analyses, conducting analyses, and preparing manuscripts as part of the interdisciplinary team.

Division of Developmental and Behavioral Health
Children's Mercy Hospital
Supervisor: Carolyn Bates, Ph.D. & Meredith Dreyer Gillette, Ph.D.

Resident Researcher *August 2020-Present*

Participating in a research study aiming to identify the impact of a new pediatric cancer diagnosis and the COVID-19 pandemic on family functioning and coping. Duties include collecting data at in-clinic oncology appointments via parent interview and questionnaires, scoring measures, preparing datasets for analyses, conducting analyses, and preparing manuscripts.

Child and Adolescent Research in Selective Mutism, Anxiety, and Absenteeism (CHARISMA) Lab- Selective Mutism August 2017-Present
University of Nevada, Las Vegas
Faculty Advisor: Christopher A. Kearney, Ph.D.

Principal Investigator
Communication and Behavior Factors in a Community Sample of Youth with Selective Mutism
There is debate in the current selective mutism literature about the typology of youth with selective mutism. Recent studies have pointed towards internalizing, externalizing, behavioral, and communication difficulties in this population. Despite this debate, there is a lack of research identifying symptom profiles in youth with selective mutism. The purpose of this study is to examine parental perception of social, emotional, and behavioral functioning and communication abilities of different children with selective mutism. This study aims to inform current assessment and intervention methods for youth with selective mutism. Data is currently being collected via an online survey. Results may have important implications for the early identification, prevention, and intervention for youth with selective mutism.

CHARISMA Lab- School Refusal
University of Nevada, Las Vegas
Faculty Advisor: Christopher A. Kearney, Ph.D.

Principal Investigator *August 2018-May 2020*
Doctoral Dissertation: Defining Problematic School Absenteeism: Identifying Youth at Risk
Defended: May 13, 2020
A precise definition of problematic school absenteeism has yet to be identified. This four-component study aims to inform absenteeism researchers, the Multi-tiered systems of support (MTSS) approach, and early assessment and intervention methods for those youth and their families at the highest risk of displaying problematic school absenteeism. Study 1 & 2 aims to review the literature of utilized definitions of problematic absenteeism and support the utilization of specific definitions for the MTSS tiers. Study 3 aims to test previous models of problematic school absenteeism, defined as 10% of full school days missed, and risk level based on family environment risk factors. Study 4 aims to test previous models of problematic school absenteeism, defined by 10% of full school days missed, and risk level based on youth psychopathology risk factors. All four components are published in Frontiers.

Lab Manager *August 2017-May 2020*
Duties included managing data collection, data organization, and analyses; preparing poster and oral presentations; coordinating publications; collaborating with community organizations and other research groups; managing lab procedures; and training and supervising up to eighteen undergraduate research assistants and six graduate students. Managed numerous research projects, including (1) Investigating the Effectiveness of a Las Vegas Truancy Diversion Program for Youth Identified as Truant; (2) Communication and Behavior Factors in a Community Sample of Youth with Selective Mutism; and (3) Identifying Youth at High Risk for Problematic Absenteeism. Created formalized laboratory procedures to increase productivity, cohesion, and effectiveness.

Principal Investigator *August 2015-August 2018*
Master's Thesis: Identifying Youth at Risk for Problematic Absenteeism Using Nonparametric Modeling: The Impact of Youth Psychopathology and Family Risk Factors
Defended: August 14, 2018
The best cutoff to differentiate problematic school absenteeism from nonproblematic school absenteeism has yet to be identified in the literature despite the need for defined cutoffs in contemporary classification systems. This study aimed to inform the MTSS approach while also contributing to early identification, assessment, and intervention methods for those youth and families at the highest risk of problematic school absenteeism and its negative consequences. This study identified subgroups of youth at the highest risk of problematic absenteeism, defined as 1% and 10% of full school days missed. Interactions among family environment and youth psychopathology risk factors were evaluated at each cutoff. Participants included 378 elementary, middle, and high school students and their families from clinic and community settings. Classification and Regression Tree (CART) procedures via SPSS decision tree software were utilized to identify profiles of youth and the most relevant family environment and youth psychopathology risk factors at each cutoff. The first set of hypotheses involved family environment factors that may predict absenteeism severity. Similarly, the second set of hypotheses involved youth psychopathology factors that may predict absenteeism severity. Hypotheses were partially supported.

Graduate Research Assistant *August 2015-August 2017*
Conducted research on the effectiveness of a Las Vegas Truancy Diversion Program for youth identified as truant. This study also evaluates truancy rates and environmental, youth, and family risk factors before and after participation in the program. Duties included conducting assessments, managing databases, executing data analysis via SPSS, conference presentations, collaborating on publications, and training and supervising research assistants. Assessments and data collection are ongoing.

The Children's Specialty Center of Nevada September 2018-March 2020
Cure 4 the Kids Foundation
Las Vegas, Nevada
Primary Supervisor: Danielle T. Bello, Ph.D.

Graduate Research Assistant
Developed data entry and management procedures for Cure 4 the Kids neuropsychology patients. This position also includes interviewing, training, and supervising a minimum of four undergraduate research assistants. Data collection and entry is ongoing.

Weiten Textbooks August 2017-January 2020
University of Nevada, Las Vegas
Faculty Advisor: Wayne Weiten, Ph.D.

Citation Editor

Assisted Dr. Wayne Weiten in completing and publishing the 11th edition of *Psychology: Themes and Variations.*

CLINICAL EXPERIENCE

Pre-Doctoral Internship: Children's Mercy Kansas City August 2020-Present
Kansas City, MO

1) Year-Long Experiences:

- **Consultation/Liaison Service**
  Primary Supervisor: Janelle Mentrikoski, Ph.D.
  Provided consultation and follow-up health and behavior assessment and intervention to hospitalized patients between 0-21 years and their families. Received referrals from general pediatrics, hematology/oncology, burn, surgery, rehabilitation, gastrointestinal, and pulmonary teams. Worked closely with multiple medical teams to coordinate patient care. Staffed evening/weekend on-call service for 6 weeks during the year.

- **Outpatient Continuity Clinic**
  Primary Supervisors: Anna Egan, Ph.D., ABPP, Elizabeth Willen, Ph.D., Megan Bolch, Ph.D., Rachel Moore, Ph.D.
  Performed diagnostic interviews, psychological assessment, and individual and family therapy for patients between the ages of 4-21 years with and without medical diagnoses. Established treatment plans using a primarily Cognitive-Behavioral Therapy (CBT) framework. Conducted targeted psychological and neuropsychological assessments. Completed case presentations, coordinated care with medical teams, and consulted with school staff.

2) Four-Month Specialty Rotations:

- **Hematology/Oncology (August-November)**
  Primary Supervisor: Lynne Covitz, Ph.D., ABPP
  Provided psychological assessment and intervention for patients between the ages of 4-21 years and their families receiving treatment in the Hematology and Oncology divisions. Care provided during inpatient hospitalization and outpatient follow-up for issues related to adjustment to diagnosis and treatment, family member coping, as well as emotional, behavioral, and family functioning. Participated in a bi-monthly sickle cell multidisciplinary clinic; provided brief cognitive, emotional, and behaviors screenings, targeted brief interventions, sickle cell education, and enrolled patients in a sickle cell persistent pain research study. Primarily utilized a Cognitive-Behavioral Therapy (CBT) framework. Conducted targeted psychological and neuropsychological assessments. Coordinated care with medical teams and consulted with school staff.

- **Neuropsychology Assessment and Cardiac Neurodevelopmental (December-March)**
  Primary Supervisor: Elizabeth Willen, Ph.D.
  Will provide neuropsychological outpatient assessments to infants and children in the cardiac neurodevelopmental program to assess the impact of cardiac issues on cognitive functions. Coordinate care with neurology and cardiology. Will participate in monthly multidisciplinary cardiac neurodevelopmental case conferences.

- **Rehabilitation for Amplified Pain Syndromes (RAPS) program (April-July)**
  Primary Supervisors: Dustin Wallace, Ph.D.

Will participate in an intensive, multidisciplinary day-program for children and teens with disabilities related to chronic pain and comorbid conversion disorders. Will provide group-based and individual therapy to children /adolescents and their families. Will provide cognitive/neuropsychological assessments, ongoing consultation, and develop behavior plans.

Volunteers in Medicine of Southern Nevada August 2019-December 2019
Las Vegas, Nevada
Primary Supervisor: Claudia Mejia, PsyD
Doctoral Practicum Student

Served as a behavioral health consultant to enhance patients' treatment prognosis. Engaged in interdisciplinary care coordination in a primary care setting. Conducted patient intakes and structured clinical diagnostic interviews, implemented evidence-based treatments to improve mental and physical outcomes, and formulated brief reports to inform treatment. Improved the integration of mental health services into primary healthcare and improved patient access to psychological services. Provided services to uninsured adults and children.

The Children's Specialty Center of Nevada/Cure 4 the Kids Foundation August 2018-May 2019
Las Vegas, Nevada
Primary Supervisor: Danielle T. Bello, Ph.D., ABPP
Doctoral Practicum Student

Conducted comprehensive neuropsychological assessments and wrote integrated reports in a pediatric hospital setting. Provided services to children and adolescents referred from oncology, hematology, rheumatology, and genetic disorder clinics. Provided brief interventions via a cognitive-behavioral orientation addressing adjustment, anxiety, depression, behavior management, medical adherence, and parent training concerns. Participated in a multidisciplinary treatment team during weekly grand rounds, sickle cell anemia clinic, and long-term follow-up clinic.

The UNLV Child School Refusal and Anxiety Disorders Clinic August 2017-May 2018
University of Nevada, Las Vegas
Primary Supervisor: Christopher A. Kearney, Ph.D.
Doctoral Practicum Student

Provided evidence-based manualized interventions to a caseload of 6-9 clients via a cognitive-behavioral orientation emphasizing exposure techniques. Services provided to diverse populations of children and adolescences between the ages of 6-16 years and their families. Utilized individual and family therapy. Clients presented with significant school-based anxiety and comorbid diagnoses. Provided targeted evidence-based assessments. Consulted frequently with school-based and medical personnel for case management. Trained and supervised six undergraduate research assistants weekly. Formalized clinic procedures were created to increase clinician organization and client satisfaction.

The PRACTICE: A UNLV Community Mental Health Center August 2016-August 2017
University of Nevada, Las Vegas
Primary Supervisor: Andrew Freeman, Ph.D.
Doctoral Practicum Student

Provided evidence-based assessment and manualized intervention to a caseload of 5-9 clients between the ages of 2-16 years and their families utilizing a primarily CBT framework. Services were provided to diverse populations. Diagnoses included both externalizing and internalizing disorders. Completed comprehensive psychological assessments.

The UNLV Child School Refusal and Anxiety Disorders Clinic August 2015-May 2016
University of Nevada, Las Vegas
Primary Supervisor: Christopher A. Kearney, Ph.D.
Graduate Assistant

Assisted advanced doctoral practicum students in providing psychological assessment and treatment to children with school-based anxieties utilizing a primarily CBT framework.

PROGRAM DEVELOPMENT

The UNLV Child School Refusal and Anxiety Disorders Clinic February 2016-May 2019
University of Nevada, Las Vegas
Primary Supervisor: Christopher A. Kearney, Ph.D.
Selective Mutism Group

An evidence-based selective mutism group treatment was adapted and formalized for the clinic utilizing behavioral, exposure, and anxiety management techniques. The group involved a parent-training portion and a child behavioral treatment portion. Services were provided to diverse populations of children between the ages of 4-8 years and their families. Conducted individual intake and post-treatment assessments for each group member as well as individual sessions with families during treatment as needed. Consulted with school-based and medical personnel weekly. Trained and supervised six undergraduate research assistants and three fellow doctoral practicum students weekly.

TEACHING EXPERIENCE

Southern Utah University August 2020-Present
Part-Time Online Instructor
Abnormal Psychology PSY 5310

Bellevue University March 2019-Present
Part-Time Online Instructor
Abnormal Psychology PY 311 & Personality Theory PY 301

University of Nevada, Las Vegas August 2017-August 2020
Graduate Student Instructor
General Psychology PSY 101 & Foundations of Social Psychology PSY 360
Taught both in-person and online courses.

University of Nevada, Las Vegas January 2017-May 2017
Teaching Assistant
Faculty Supervisor: Mary Powell, Ph.D.
Motivation and Emotion PSY 412 & Personality PSY 435

OTHER APPLICABLE TEACHING EXPERIENCE

Workshop Leader October 2018, April 2018, November 2017
University of Nevada, Las Vegas

Outreach Undergraduate Mentoring Program (OUMP)
Applying to Graduate School

Developed a workshop on the "nuts and bolts" of graduate school application preparation and completion process focusing on experimental psychology and clinical psychology.

Workshop Leader December 2017
University of Nevada, Las Vegas
Outreach Undergraduate Mentoring Program (OUMP)
Study and Writing Skills

Developed a workshop on research relevant to study and writing skills for underrepresented psychology majors within the psychology department.

SELECT SUPPLEMENTAL PROFESSIONAL TRAINING

Comprehensive Training in Dialectical Behavior Therapy (DBT): Part I Theory, Structure, Targets and Treatment Strategies Alan Fruzzetti, Ph.D. September 2019
3-day training on the theoretical foundation and implementation of DBT for psychologists.

LEADERSHIP AND SERVICE

Diversity Graduate Assistant
Diversity and Inclusion Committee 2019-2020

American Psychological Association (APA), Division 54 Pediatric Psychology
Network of Campus Representatives (NCR) 2019-2020

Clinical Student Committee (CSC)
University of Nevada, Las Vegas
President 2018-2019
Treasurer 2016-2017
Secretary 2015-2016
Cohort Representative 2015-2018; 2019-2020

Outreach Undergraduate Mentoring Program (OUMP)
University of Nevada, Las Vegas
Graduate Student Mentor 2015-2020
Workshop Leader 2017-2018

Selective Mutism Association (SMA)
National Board Member 2017-2019

Nevada Psychological Association (NPA)
Las Vegas, Nevada
Graduate Student Volunteer 2018-2019

Graduate & Professional Student Association (GPSA)
University of Nevada, Las Vegas 2014-2015

Psychology Department Representative

PROFESSIONAL AFFILIATIONS

Cardiac Neurodevelopmental Outcome Collaborative (CNOC) Diversity and Inclusion Special Interest Group (SIG)	2020-Present
APA Division 53: Society of Child & Adolescent Psychology	2019-Present
APA Division 54: Society of Pediatric Psychology	2019-Present
Selective Mutism Association	2017-Present
Association of Behavioral and Cognitive Therapies (ABCT)	2017-Present
APA Division 2: Society for the Teaching of Psychology (STP)	2017-Present
American Psychological Association (APA)	2016-Present
American Psychological Association of Graduate Students (APAGS)	2016-Present
Association for Psychological Science (APS)	2017-2019
Nevada Psychological Association (NPA)	2016-2019
Society for Police and Criminal Psychology (SPCP)	2015-2016

PROFESSIONAL REFERENCES

Anna Egan, Ph.D., ABPP
Division of Developmental and Behavioral Health,
Section of Psychology
Director of Psychology Training
Children's Mercy Kansas City
Professor, Department of Pediatrics
UMKC School of Medicine
2401 Gillham Road Kansas City, MO 64108
Phone: (816) 234-3674
E-mail: aegan@cmh.edu

Christopher A. Kearney, Ph.D.
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