ABSTRACT

Title of Document:	PREDICTORS OF STUDENT REFERRALS TO PROBLEM-SOLVING TEAMS: CHILD STUDY TEAMS AND INSTRUCTIONAL CONSULTATION TEAMS
	Kristi S. Maslak, Doctor of Philosophy, 2015
Directed By:	Associate Professor Emeritus William Strein, D.Ed. Department of Counseling, Higher Education, and Special Education

This study identified predictors of elementary school student problem-solving team referrals from among a broad range of student and teacher measures, including student demographic characteristics, services received, academic achievement, behavior, and student-teacher relationship quality, as well as teacher demographic characteristics, education and experience, and beliefs and practices. The participant sample included first through fifth grade students ($n = 13,025$) and their classroom teachers ($n = 570$) within schools ($n = 26$) concurrently implementing two problem-solving team models that differed in theoretical framework, focus, and process: Child Study Teams (CS Teams: Moore, Fifield, Spira, & Scarlato, 1989) and Instructional Consultation Teams (IC Teams: Rosenfield & Gravois, 1996). Using multinomial hierarchical general linear modeling (HGLM) and the Hierarchical Linear Modeling program (HLM 7.01: Raudenbush et al., 2011), statistically significant effects were found for student sex;

Hispanic race/ethnicity; reading, writing, and math achievement; prior ratings of classroom concentration; and closeness in the prior student-teacher relationship on student referrals to both problem-solving teams relative to not being referred to a problem-solving team. Student African American and Unspecified/Other race/ethnicity, prior internalizing behavior problems, teacher sex, teacher age, and 11+ years of total teaching experience uniquely statistically significantly predicted referrals to CS Teams. Student Asian race/ethnicity, being a new student to the district, receiving special education services the prior school year, having a conflict laden relationship with the prior teacher, and 11+ years of teaching experience at the current school uniquely statistically significantly predicted referrals to IC Teams. Planned post hoc coefficient contrasts compared the predictors of student referrals to IC Teams and CS Teams. Findings indicate that student sex and race/ethnicity, being new to the district, receiving special education the prior school year, relationship quality with the prior teacher, severity of academic or behavior problems, and teacher age statistically significantly differentiated referral between the two problem-solving teams. However, with odds ratios ≤ 2.5, the sizes of all effects in this study were small (Chen, Cohen, & Chen, 2010; Chinn, 2000). Limitations include generalizability, missing data, model misspecification, and constraints of standard statistical analysis software.

PREDICTORS OF STUDENT REFERRALS TO PROBLEM-SOLVING TEAMS:
CHILD STUDY TEAMS AND INSTRUCTIONAL CONSULTATION TEAMS

By

Kristi S. Maslak, M.A., AGS

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Advisory Committee:
Associate Professor Emeritus William Strein, Chair
Clinical Assistant Professor Jill Berger
Associate Professor Robert Croninger
Associate Professor Jeffrey Harring
Professor Emerita Sylvia Rosenfield

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Correspondence concerning this dissertation should be addressed to Kristi S. Maslak, Department of Counseling, Higher Education, and Special Education, University of Maryland, College Park, MD 20742. Email: kmaslak@umd.edu

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Chapter 1: Rationale

Introduction

The Education for All Handicapped Children Act (1975), or P.L. 94-142, established that children with disabilities have the right to a free and appropriate education. Additionally, the act charged local education agencies with the responsibility of finding and evaluating children with disabilities, and it guaranteed federal funding to support the development and maintenance of special education services that meet the diverse needs of disabled children.

During the late 1970's and early 1980's, several alarming trends with special education eligibility emerged. First, each year approximately 5% of all school age children were being suspected of having a disability, 95% of these children were recommended for evaluation, and 75% were subsequently found eligible for special education, which resulted in substantial annual increases in the special education rolls (Algozzine, Christenson, & Ysseldyke, 1982). Second, the number of eligible children began to exceed probable base rates within the population, particularly among soft disabilities, such as intellectual and learning disabilities, which often lack a clear biological cause and rely heavily on clinical judgment for their identification (Chalfant, Pysh, & Moultrie, 1979; Kovaleski, 2002; Nellis, 2012). Third, culturally and linguistically diverse students were being disproportionately represented among these soft disabilities, but not the hard disabilities, such as visual or hearing impairment, which generally have a clear biological cause and their identification is less reliant on clinical judgment (Albrecht, Skiba, Losen, Chung, & Middleberg, 2011; Artiles, Kozleski, Trent, Osher, & Ortiz, 2010; Chu, 2011; Dyches & Prater, 2010).

According to Kovaleski (2002), leaders within the field of education suspected that these special education eligibility trends were due to the inappropriate referral and subsequent misidentification of non-disabled, struggling students whose needs were not being met effectively within the general education learning environment. Proposed solutions for addressing this problem centered on the development of classroom-based interventions and approaches for supporting general education teachers' efforts to deliver and differentiate instruction. By focusing on improving instructional supports for struggling students within the context of the general education learning environment, it was reasoned that the types of difficulties contributing to the referral of non-disabled, struggling students for special education eligibility would be reduced or prevented (Chalfant et al., 1979; Graden, Casey, & Christenson, 1985; Rosenfield, 1987).

The importance of providing struggling students with interventions inside of the general education setting gained increasingly broad support during the 1980's and 1990's, and it was eventually reflected in federal legislation with the reauthorization of P.L. 94-142, renamed the Individuals with Disabilities Education Act (IDEA, 1997). Included in this reauthorization were requirements that local educational agencies first attempt interventions prior to considering students for special education eligibility. These requirements were further strengthened by provisions in a subsequent reauthorization (IDEA, 2004), which permitted the allocation of special education funds to support intervention efforts.

Decisions about the nature, scope, and method of delivering interventions consistent with IDEA (2004) remain under the purview of states and local educational agencies (Buck, Polloway, Smith-Thomas, & Cook, 2003). However, multidisciplinary

school-based teams of professionals, including general education teachers, specialists, and administrators, are the most common vehicle through which intervention supports are provided to struggling students within the general education setting (Slonski-Fowler & Truscott, 2004). In fact, when Truscott, Cohen, Sams, Sanborn, and Frank (2004) surveyed departments of education across the 50 states and the District of Columbia, 86% had statutes that either required or recommended school-based team processes to ensure the implementation of interventions consistent with IDEA (2004).

Throughout the literature, these multidisciplinary school-based teams have commonly been referred to as pre-referral teams, intervention teams, and problem-solving teams. In this study, the preference is for the term *problem-solving team* for two primary reasons. Although the teams play a role within the process for determining special education eligibility, student referral to special education following involvement with the team is not inevitable, and student eligibility for special education services does not preclude a teacher from seeking team support about a student concern; therefore, the term *pre-referral* is somewhat inaccurate and misleading (Bahr & Kovaleski, 2006; Kovaleski, 2002). Furthermore, the term *problem-solving* best reflects the functional purpose of the teams, which includes collecting information, discussing student concerns, identifying interventions, monitoring progress, evaluating intervention effectiveness, and if necessary, making referrals for special education eligibility or other supports once general education resources have been exhausted (Burns, Vanderwood, & Ruby, 2005).

Several different models of problem-solving teams have been proposed, including Child Study Teams (Moore et al., 1989), Instructional Consultation Teams (Rosenfield & Gravois, 1996), Instructional Support Teams (Kovaleski, Tucker, & Duffy, 1995),

Intervention Assistance Teams (Graden, 1989), Mainstream Assistance Teams (Fuchs, Fuchs, & Bahr, 1990), Prereferral Intervention Teams (Graden et al., 1985), Student Assistance Teams (House & McInerney, 1996), and Teacher Assistance Teams (Chalfant et al., 1979). The primary purpose, basic assumptions, and broad goals of the teams are generally shared across models. Each problem-solving team model has the primary purpose of helping struggling students to succeed within the general education setting by identifying appropriate interventions and supporting the efforts of general education teachers to deliver effective instruction (Slonsky-Fowler & Truscott, 2004). The models assume that (a) all children can learn; (b) collaboration among team members is essential; (c) the purpose of the team is to solve rather than identify problems; and (d) decisions are based on data (Burns et al., 2005). Furthermore, the broad goal of each model is to reduce the number of inappropriate referrals for special education eligibility, or the referral of students whose needs can be met effectively within the general education setting.

Despite the similarities of purpose, basic assumptions, and broad goals across problem-solving team models, there are some meaningful differences regarding their theoretical frameworks, focus and process of problem-solving, and approach for intervention implementation. The two problem-solving team models included in this study, Instructional Consultation Teams (IC Teams: Rosenfield & Gravois, 1996) and Child Study Teams (CS Teams: Moore et al., 1989) highlight some of these differences.

Instructional consultation teams. IC Teams (Rosenfield & Gravois, 1996) were developed to support the delivery of Instructional Consultation (IC: Rosenfield, 1987): an integrated model of school-based consultation that fuses the consultee-centered approach

of mental health consultation with the systematic, data-based problem solving approach of behavioral consultation. Specifically, IC Teams are multidisciplinary school-based teams that include general educators, special educators, school administrators, and specialists who are trained in the process of IC. IC Teams differ from most other problem-solving team models in that a case management approach to problem-solving is followed. In other words, problem-solving takes place during meetings between an individual team member serving as the case manager and a teacher requesting assistance rather than during team meetings (Rosenfield & Gravois, 1996, 1999). Therefore, IC Teams meetings function as a resource for coordinating teacher support requests, ongoing professional development for team members, and targeted case problem-solving when requested.

The theoretical framework that grounds the focus and process of problem-solving supported through IC Teams is clearly defined. According to Rosenfield (1987, 1995, 2008), learning in the classroom occurs through an interaction among a student's prior knowledge, task demands, and delivered instruction. When a student fails to meet teacher expectations for learning, IC assumes an ecological mismatch among elements of this three-part instructional triangle (Gravois, Rosenfield, & Gickling, 1999). Therefore, identifying the instructional mismatch and creating balance, not the identification of student skill deficits, is the focus of problem-solving. Additionally, as a consultee-centered model of consultation, IC focuses on fostering a collaborative relationship between a case manager and referring teacher, as well as engaging and enhancing a teacher's repertoire of skills for ensuring an instructional match when delivering instruction.

Consistent with IC's grounding in behavioral consultation, the process of IC is systematic and data-based. Specifically, an IC Teams case manager and referring teacher clarify concerns and match interventions to meet student needs through five stages: (a) contracting, (b) problem identification and analysis, (c) intervention planning, (d) intervention implementation and evaluation, and (e) closure (Rosenfield, 1987; 2008). At contracting, the case manager explains the assumptions of IC and describes the collaborative, data-based process. During problem identification and analysis, the teacher and case manager operationally define the presenting problem within the context of the instructional triangle (Gravois et al., 1999), use Instructional Assessment (Gravois & Gickling, 2008) to establish a baseline measure of the student's performance, and clarify performance goals. Throughout the intervention planning and implementation stages, the teacher and case manager pool knowledge about research-based instructional practices to design and implement targeted interventions, regularly collect data to monitor student progress, and evaluate intervention effectiveness. During the final stage, closure, the teacher and case manager agree to end the consultation because stated goals are successfully attained or because both agree that a referral for additional support services, such as special education, is warranted. Therefore, teachers are highly involved with the problem-solving and intervention process, and support is provided regularly.

Child study teams. The CS Teams model described in Moore et al. (1989) was a multidisciplinary, school-based team charged with making decisions about special education evaluations and eligibility. However, with the increasing role of problem-solving teams, particularly following IDEA (1997), many local educational agencies adapted their CS Teams to serve as problem-solving intervention teams and reserved

special education decisions for an Individualized Education Plan Team. In fact, when the departments of education in the 50 states and the District of Columbia were surveyed, 27 (53%) indicated that a standard term was used to describe their IDEA (1997) compliant intervention team process, and CS Teams was among the standard terms applied (Buck et al., 2003). These problem-solving CS Teams have no formal written literature describing theoretical frameworks, processes, or procedures beyond the general goals and functions of all problem-solving teams. Therefore, CS Teams are often defined locally according to district or school policy.

In the current study, the school district's administrative procedures outline the basic role and structure of their CS Teams. Specifically, the CS Teams are described as a "multidisciplinary problem-solving team" that "meets regularly to identify, implement, and make recommendations related to specific student needs" (Prince William County Public Schools, 2010, p. 10). Within each school, the CS Teams are required to include an administrator, the person making the referral, one of the student's teachers, a specialist in the area of need, and a case manager. The case manager is a team member other than a special educator or referring teacher who is expected to provide post-meeting support regarding the collection of student data, dissemination of developed intervention plans, and communication of student progress. No further information about the processes, procedures, or responsibilities of the CS Teams or team members is provided.

As described, it is evident that the district's CS Teams were not grounded within a theoretical framework and followed a group meeting approach to problem-solving, as do most other problem-solving team models (Iverson, 2002; Burns et al., 2005). With a group meeting approach, the discussion of student concerns and the identification of

interventions take place within the context of team meetings, and follow-up meetings are held to share student progress and determine next steps. During the CS Teams meetings, problem-solving focused on identifying and ameliorating student skill deficits, and the discussion of interventions were somewhat unstructured and limited to a set of basic instructional strategies or available intervention programs within a school. (V. Fornasar, personal communication, September 21, 2014). Students identified as being in need of support were either scheduled to work with a specialist, or their teachers were expected to implement recommended classroom-based interventions independently with limited follow-up support. Therefore, the amount of teacher involvement with the problem-solving and intervention process above and beyond attending team meetings varied depending on the recommendation of the CS Team.

Statement of the Problem

Previous research suggests that school-based problem-solving teams are effectively reducing the overall number of special education referrals (Burns & Symington, 2002; McNamara, 1998; McNamara & Hollinger, 1997) as well as the disproportionate special education referrals of culturally and linguistically diverse students (Gravois & Rosenfield, 2002; 2006), particularly when teams are linked with University-based programs or research efforts (Sarfan & Sarfan, 1996; Yetter, 2010). Therefore, as would be expected given the common role of problem-solving teams in meeting intervention requirements outlined in IDEA (2004), referral to problem-solving teams influences the likelihood that students will later be considered for special education. However, not all struggling students are served through problem-solving teams. Furthermore, culturally and linguistically diverse students continue to be

disproportionately represented in special education (Artiles et al., 2010; Artiles, Reuda, Salazar, & Higareda, 2005; Council for Children with Behavioral Disorders [CCBD], 2013; Hosp & Reschly, 2004; Sullivan, 2011; Sullivan & Bal, 2013), and concerns about intentional or unintentional bias in both general and special education referral and decision-making processes have been raised (CCBD, 2013; Mamlin & Harris, 1998).

Identifying predictors of student referrals to problem-solving teams can provide information useful for determining and ensuring the equitable provision of intervention supports to struggling students within the general education setting. Identifying the characteristics of students that predict student referrals to problem-solving teams can provide information about students who are more likely to receive interventions, students who may be underserved, and whether culturally and linguistically diverse students have equal access to interventions. Identifying the characteristics of teachers that predict student referrals to problem-solving teams can provide information about teachers who are more likely to refer students for intervention supports, as well as teachers who may underutilize problem-solving teams. The information about student and teacher characteristics that increase and decrease the likelihood of student referrals to problem-solving teams can then be used to target outreach, training, and support efforts designed to ensure that all struggling students have equal access to interventions within the general education setting.

Considering that student academic and behavior difficulties are the primary reasons provided by teachers as their basis for referral (Briesch, Ferguson, Volpe, & Briesch, 2010; Del'Homme, Kasari, Forness, & Bagley, 1996; Lloyd, Kauffman, Landrum, & Roe, 1991), one would expect that measures of student achievement and

behavior statistically significantly predict student referrals to problem-solving teams. Additionally, given the disproportionate representation of culturally and linguistically diverse students in special education (Artiles et al., 2005, 2010; CCBD, 2013; Hosp & Reschly, 2004; Sullivan, 2011; Sullivan & Bal, 2013) and concerns about bias in teachers' referral decisions (CCBD, 2013; Mamlin & Harris, 1998), one would expect that other characteristics of students and teachers currently predict student referrals to problem-solving teams above and beyond student achievement and behavior.

Unfortunately, there is a paucity of research on predictors of student referrals to problem-solving teams such that only one quantitative study (Pas, Bradshaw, Hershfeldt, & Leaf, 2010) on the subject was identified during a review of the literature published in peer-reviewed journals within the past 20 years. Findings from this study suggest that student behavior as well as personal characteristics of students and teachers indeed predict student referrals to problem-solving teams. Using multilevel modeling to account for the nesting of students within teachers and schools, Pas et al. (2010) found a statistically significant relationship between student concentration behaviors and student problem-solving team referrals. Furthermore, statistically significant, independent relationships with problem-solving team referrals were found for student sex, student eligibility for free and reduced meals, teacher sex, and teacher efficacy. However, the primary focus of Pas et al. was on the effect of teacher efficacy and burnout on student referrals, and as such, only a few key student and teacher characteristics were included as covariate controls. Additionally, a major limitation of Pas et al. was the evaluation of student problem-solving team referrals without considering the effect of student academic

achievement, one of the two primary reasons teachers provide as their basis of referral (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991).

At this time, the peer-reviewed literature on predictors of student referrals to problem-solving teams is extremely limited in number and scope. The relationship among student referrals to problem-solving teams and both student achievement and behavior, the two primary reasons teachers provide as their basis for making a referral (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991) has yet to be considered. Additionally, the independent effect of student and teacher characteristics on student referrals to problem-solving teams above and beyond the effect of both student achievement and behavior has yet to be considered. In order to broaden and strengthen the body of literature on predictors of student referrals to problem-solving teams, new research is needed that considers the effect of student and teacher characteristics while also considering the effect of student academic achievement and behavior.

Purpose of the Current Study

The primary purpose of this study was to identify predictors of elementary school student referrals to problem-solving teams using multilevel modeling to account for the nesting of students within teachers and schools, and a broad range of student and teacher characteristics. Considering the limited availability of prior research on the subject, this study is exploratory in nature and describes, but does not provide a causal explanation for, the student and teacher characteristics relevant for student problem-solving team referrals. Given that academic and behavior difficulties are the primary reasons provided by teachers as their basis for referral (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991), it was expected that measures of student academic achievement and

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behavior would statistically significantly predict student referral to problem-solving teams. Therefore, this study included measures of student academic achievement and behavior as predictors. Additionally, student and teacher characteristics that have been identified in the literature as having statistically significant relationships with student academic achievement and behavior were included as predictors to determine if they had an independent effect on student referrals. Student characteristics included demographic characteristics, support services being received, and student-teacher relationship quality. Teacher characteristics included demographic characteristics, education and experience, and beliefs and practices.

This study was conducted in a school district that was concurrently implementing two different problem-solving team models: IC Teams (Rosenfield & Gravois, 1996) and CS Teams (Moore et al., 1989). The two models differed with respect to their focus of concern, forum and process of problem-solving, teacher involvement in the problem-solving and intervention process, and extent of follow-up support provided to teachers. Specifically, IC Teams focused on engaging and enhancing teacher skills to address instructional mismatches and used a structured process within the context of regular meetings between a case manager and referring teacher to discuss problem-solving and intervention development, while CS Teams focused on addressing student skill deficits and used an unstructured format within the context of team meetings to discuss problem-solving and intervention development. Additionally, with IC Teams, teachers were highly involved with the problem-solving and intervention process, and follow-up support was provided regularly; however, with CS Teams, teacher involvement with the problem-solving and intervention process was limited, as was follow-up support. Given the

differences between the two problem-solving teams and that teachers had the choice of team when making referral decisions, it was suspected that the teams may have appealed differently to teachers based on their beliefs and practices. Furthermore, it was suspected that student-teacher relationship quality might influence whether teachers are willing to commit to the increased involvement associated with IC Teams. Therefore, the secondary purpose of this study was to identify and compare the student and teacher characteristics that predicted student referrals to IC Teams and CS Teams.

Research Questions

Question 1. Compared with students who were not referred to a problem-solving team, what characteristics of students, namely demographic characteristics, services being received, prior student-teacher relationship quality, academic achievement, and prior classroom behavior, predict student referral to (a) the Instructional Consultation Team and (b) the Child Study Team?

Question 2. What characteristics of teachers, namely demographic characteristics, education and experience, and beliefs and practices, predict student referral to (a) the Instructional Consultation Team and (b) the Child Study Team relative to students who were not referred to a problem-solving team?

Question 3. Do the relationships between student characteristics and student referral to (a) the Instructional Consultation Team and (b) the Child Study Team relative to not being referred to a problem-solving team vary as a function of teacher characteristics? If so, what characteristics of teachers moderate the relationship between student characteristics and referral?

Question 4. What characteristics of students and teachers differentially predicted

student referral to Instructional Consultation Teams and Child Study Teams?

Chapter 2: Review of Literature

Introduction

This chapter reviews the literature relevant to the study of student and teacher characteristics that predict student referrals to problem-solving teams. The first section reviews the available literature on characteristics of students and teachers associated with student academic achievement and behavior, which are the two primary reasons teachers provide as their basis for referral (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991). Within this section, student characteristics are reviewed first followed by a review of teacher characteristics. The second section reviews the available literature on predictors of student referrals to problem-solving teams, and the third section reviews the available literature on predictors of student referrals to special education. Although students referred to problem-solving teams and special education are somewhat different sample populations, the literature on predictors of referral to special education was reviewed to supplement the scant literature on predictors of referral to problem-solving teams and provide information about factors relevant to the referral of struggling students.

The reviewed literature was identified through systematic title searches in several electronic databases, including Academic Search Complete, PsycARTICLES, PsycINFO, Psychology & Behavioral Sciences Collection, Education Source, and ERIC. Following the title searches, abstracts were reviewed to determine literature relevance. With the emerging role of problem-solving teams during the 1980's and their increasingly important role since IDEA (1997), it was determined that literature prior to 1995 would not likely yield information relevant to the current investigation. Additionally, the current investigation involves elementary school students and their teachers. Therefore,

the search was limited to literature available in peer reviewed journals within the past 20 years that involved school age children. The literature on predictors of student referrals to problem-solving teams and special education was further limited to studies that applied quantitative research methods to evaluate teachers' referral decisions. Studies that applied qualitative methods were excluded due to uncertainty about the validity of their inferences given their reliance on interviews as a primary data source and concerns expressed in the literature that teachers may be unaware of their own biases when making referral decisions (CCBD, 2013; Mamlin & Harris, 1998). Table summaries of the reviewed literature on characteristics of students and teachers associated with student academic achievement and behavior, predictors of student referrals to problem-solving teams, and predictors of student referrals to special education are presented in Appendices A through H.

Correlates of Student Achievement and Behavior

The academic content areas traditionally considered most educationally important and foundational are the three R's: reading, writing, and arithmetic. Additionally, the most common student behavior problems reported by teachers involve externalizing, internalizing, and inattentive behaviors (Harrison, Vannest, Davis, & Reynolds, 2012). Therefore, search terms for identifying literature pertaining to student academic achievement included *achievement, reading, writing, arithmetic,* and *math*. Search terms for identifying literature pertaining to student behavior included *behavior, internalizing, externalizing, attention,* and *concentration*. In the sections that follow, the search terms and findings from the literature on student and teacher characteristics associated with student academic achievement and behavior are summarized.

Student characteristics. Student characteristics that were considered for their association with student academic achievement and behavior included demographic characteristics, school support services received, and student-teacher relationship quality. The following demographic characteristics, or personal qualities of the student, were considered: sex, race/ethnicity, and age. Search terms for identifying literature pertaining to student demographic characteristics were *student* with *sex, gender, age, old for grade, young for grade, race, ethnicity, white, Caucasian, black, African American, Asian, Hispanic, Latino,* and *Latina*.   The following school support services were considered: free and reduced meals (FARM), English as a second or other language (ESOL), and special education. Search terms for identifying literature pertaining to school support services were *student* with *free reduced meal, poverty, socioeconomic,* and *income* for FARM; *second language, language learner, limited English, dual language, language minority, and bilingual* for ESOL; and *special education.* The additional search terms were included when identifying literature for FARM and ESOL to ensure that the population of students the services are intended to support were considered. Finally, student-teacher relationship quality was considered. Search terms for identifying literature pertaining to student-teacher relationship quality were *student* and *teacher* with *relationship, close,* and *conflict.*

Demographic characteristics. Several studies have evaluated the effect of student demographic characteristics, including sex, race/ethnicity, and age, on student academic achievement or behavior. Regarding the effect of student sex on academic achievement, statistically significant, positive effects of being female have been found for norm-referenced measures of reading and writing achievement (Scheiber, Reynolds,

Hajovsky, & Kaufman, 2015), as well as specific reading and math skills, including letter-word identification, reading fluency, geometry, and math fact accuracy (Lachance & Mazzocco, 2006). Statistically significant, positive effects of being male have been found for math skills associated with numeration and knowledge of time and money (Lachance & Mazzocco, 2006). However, it should be noted that some studies have not found any statistically significant differences between student sex and academic achievement. For example, Scheiber et al. (2015) found no statistically significant differences between male and female students on norm-referenced measures of math achievement, and McIntosh, Reinke, Kelm, & Sadler (2013) found no statistically significant differences between male and female students on norm-referenced measures of oral reading fluency.

The literature on the relationship between student sex and behavior reveals statistically significant, but somewhat conflicting, results. Specifically, Peters, Kranzler, Algina, Smith, and Daunic (2014) found that teachers rated male students lower on measures of externalizing and internalizing behaviors, and higher on measures of social skills and overall competence compared with female students. In contrast, Miner and Clarke-Stewart (2008) found that teachers rated male students higher on measures of externalizing behaviors than female students. Additionally, McIntosh et al. (2013) found that the frequency of office disciplinary referrals statistically significantly increased from kindergarten through the fifth grade for male, but not for female, students.

Several studies have found a statistically significant relationship between student race/ethnicity and student academic achievement or behavior; however, the direction of the relationship has varied across racial/ethnic categories. Compared with Caucasian

students, teachers rate Asian students higher on measures of academic effort and academic proficiency (Hsin & Xie, 2014), but Hispanic students lower on measures of student learning, motivation, creativity, and leadership (Plata & Masten, 1998). With respect to teacher ratings of student behavior, and as compared with Caucasian students, Hispanic students are rated as less internalizing (Peters et al., 2014), while African American students are rated as more externalizing (Miner & Clarke-Stewart, 2008; Peters et al., 2014) with lower social skills, overall competence (Peters et al., 2014), and effective habits of work (Downey & Pribesh, 2004).

Finally, several studies have evaluated the effect of student age at entry to kindergarten on later student academic achievement or behavior. Compared with students who are younger or young for grade at entry to kindergarten, older or old for grade students perform better on norm-reference measures of kindergarten reading and math skills (Stipek & Byler, 2001) as well as criterion-referenced measures of early literacy skills (Huang & Invernizzi, 2012), and teacher ratings of literacy and mathematical thinking (NICHD Early Child Care Research Network [NICHD], 2007). However, the younger or young for grade students made greater gains (NICHD, 2007; Huang & Invernizzi, 2012) such that the effect of student age on academic achievement was no longer statistically significant by the end of the third grade (Stipek & Byler, 2001). With respect to student behavior, NICHD (2007) found no statistically significant effects of kindergarten entry age on teacher ratings of externalizing and internalizing problems, or on ratings of social competence. However, Crothers et al. (2010) found that teachers rated students who were old for grade as presenting with more bullying and

victim behaviors than other students, suggesting that old for grade students are at increased risk for involvement in bully-victim conflicts.

School support services. Several studies have evaluated the effect of school support service eligibility for FARM, ESOL, and special education, on student academic achievement and behavior. The literature pertaining to FARM eligibility either included FARM status as a measure or considered the underlying reasons that students qualify for the service, namely family income and poverty. Similarly, the literature pertaining to ESOL eligibility either included ESOL status as a measure or considered the underlying reasons why students qualify for the service, namely having a primary language other than English or limited English proficiency. Furthermore, it should be noted that each of the identified studies that considered the relationship between ESOL eligibility and student academic achievement or behavior evaluated the relationship as it pertained to students whose primary language was Spanish, and the studies that considered the relationship between special education eligibility and student academic achievement or behavior evaluated the relationship as it pertained to students with high incidence disabilities, such as specific learning disability, speech or language impairment, and emotional disability.

Recent research suggests that family income has a statistically significant, positive effect on student reading skills at kindergarten entry, as well as gains in student reading achievement from the third through eighth grade (Kieffer, 2012). Additionally, poverty and eligibility for FARM have been found to have a statistically significant, negative effect on norm-referenced measures of student math achievement (Burnett & Farkas, 2008) and teacher ratings of student emotional competence (Peters et al., 2014).

Moreover, Henninger and Luze (2012) found a statistically significant interaction between time in poverty and student sex such that increased time in poverty was associated with higher ratings of externalizing behavior problems among female, but not male, students. Although Peters et al. (2014) did not find a statistically significant main effect of FARM eligibility on teacher ratings of student social skills or externalizing and internalizing behavior problems, Dearing, McCartney, and Taylor (2006) found a statistically significant, positive relationship between chronic poverty and teacher ratings of student externalizing and internalizing behavior problems.

Among non-native English speaking students, the literature suggests that initial academic achievement for early literacy skills is lower upon entry to kindergarten (Kieffer, 2008) and at the end of first grade (Kieffer & Vukovic, 2013) compared with native English speakers. Although, non-native English speaking students make statistically significantly greater gains in reading achievement during the early elementary years compared with native English speakers (Kieffer, 2008; 2011), these gains are limited to the year following oral English proficiency acquisition (Kieffer, 2011) such that overall gains in reading skills between the first and fourth grades do not statistically significantly differ between native and non-native English speakers (Kieffer & Vukovic, 2013). With respect to measures of student behavior, findings indicate that teachers rate non-native English speakers statistically significantly lower on measures of externalizing behaviors (Dawson & Williams, 2008; Han, 2010), internalizing problems (Dawson & Williams, 2008), and interpersonal skills (Han, 2010) compared with native English speakers during the early elementary years. However, by the fourth grade, teachers rated non-native English speaking students as presenting with statistically

significantly higher externalizing behavior problems than native English speakers (Dawson & Williams, 2008).

Finally, the literature suggests that initial academic achievement and rate of learning is lower for special education students compared with general education students. Specifically, among second through sixth grade students, Christ, Silberglitt, Yeo, and Cormier (2010) found that special education students made statistically significantly lower gains than general education students on curriculum based measures of oral reading fluency over a one-year period. Additionally, Schulte and Stevens (2015) found that students who were currently or previously determined eligible for special education services made statistically significantly lower gains than general education students on criterion-referenced measures of math achievement from third to seventh grade.

Student-teacher relationship quality. Student-teacher relationship quality refers to the extent that students and teachers share a warm, caring, and supportive relationship (Hamre & Pianta, 2006; Pianta, 2009). Consistent with attachment theory (Bowlby, 1982), it is believed that the relationship between individual students and their teachers provides the foundation on which students build self-confidence, explore the school environment, and learn to adapt to the changing academic and social demands of schooling. Indeed, studies conducted within an elementary school setting have found statistically significant, positive relationships between student-teacher relationship quality and student academic performance, including reading achievement (Baker, 2006) and teacher ratings of overall academic performance (Fowler, Banks, Anhalt, Der, & Kalis, 2008). Specifically, sharing a close student-teacher relationship is positively associated

with student reading achievement (Baker, Grant, & Morlock, 2008) and academic readiness (Birch & Ladd, 1997). Additionally, improvements in closeness of the student-teacher relationship between the first and fifth grades are associated with gains in student reading achievement (McCormick & O'Connor, 2015). However, sharing a student-teacher relationship characterized by conflict is negatively associated with student reading achievement (Baker et al., 2008; McCormick & O'Connor, 2015), work habits, and classroom adjustment (Baker et al., 2008).

Statistically significant, positive relationships have also been observed between student-teacher relationship quality and student behavior, including classroom adjustment and social skills (Baker, 2006). Specifically, sharing a close student-teacher relationship is positively associated with student classroom adjustment (Baker et al., 2008), school liking (Birch & Ladd, 1997), and prosocial behavior (Fowler et al., 2008); and it is negatively associated with student externalizing behavior (Fowler et al., 2008). In contrast, sharing a student-teacher relationship that is characterized by conflict is positively associated with student externalizing behavior (Fowler et al., 2008), and it is negatively associated with student work habits and classroom adjustment (Baker et al., 2008), class participation (Birch & Ladd, 1997), and prosocial behavior (Fowler et al., 2008). Furthermore, studies suggest that a positive student-teacher relationship serves as a protective factor for students who present with externalizing behavior problems. Specifically, Baker (2006) and Baker et al. (2008) found that among students with externalizing behaviors, reading achievement was higher for those that had a positive student-teacher relationship.

Teacher characteristics. Teacher characteristics that were considered for their association with student academic achievement and behavior included demographic characteristics, education and experience, and beliefs and practices. The following demographic characteristics, or personal qualities of the teacher, were considered: sex, race/ethnicity, and age. Search terms for identifying literature pertaining to teacher demographic characteristics were *teacher* with *sex, gender, race, ethnicity, white, Caucasian, black, African American, Asian, Hispanic, Latino, Latina,* and *age*. The following education and experience characteristics were considered: highest degree attained and years teaching. Search terms for identifying literature pertaining to teacher education and experience were *teacher* with *education, degree, training, qualification,* and *experience*. Finally, the following beliefs and practices were considered: teacher efficacy, collaboration, job satisfaction, and instructional practices. Search terms for identifying literature pertaining to teacher beliefs and practices were *teacher* with *efficacy, collaboration, job satisfaction,* and *instructional practices*.

Demographic characteristics. Several studies have evaluated the effect of teacher sex, race/ethnicity, and age, on student academic achievement and behavior. Specifically, Taylor, Gunter, and Slate (2001) found that compared with female teachers, male teachers who observed students in scripted, videotaped scenarios rated African American female students as presenting with more significant problem behaviors than Caucasian or male students. When rating a largely African American, low income student population, and as compared with Caucasian teachers, African American teachers have been found to hold more positive academic expectations (Pigott & Cowan, 2000), rate students higher on measures of prosocial behavior (Fowler et al., 2008) and social

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competence (Pigott & Cowan, 2000), and rate students lower on measures of problem behavior (Pigott & Cowan, 2000). Although Fowler et al. (2008) found no statistically significant main effect of teacher race/ethnicity on ratings of student mathematical thinking, literacy development, or externalizing behavior, Downey and Pribesh (2008) found a statistically significant interaction between teacher race/ethnicity and student race/ethnicity such that compared with African American teachers, Caucasian teachers rated Caucasian students as presenting with fewer externalizing problems than African American students. Similarly, Croninger, Rice, Rathbun, and Nishio (2007) found no statistically significant main effect of teacher age on first grade student gains in reading or math achievement; however, Peters et al. (2014) found a statistically significant interaction between teacher age and student sex such that differences between male and female student ratings for externalizing problems lessened as teacher age increased.

Education and experience. The most recent reauthorization of the Elementary and Secondary Education Act of 1965, known more commonly as No Child Left Behind (NCLB, 2002), requires that teachers in core academic subjects meet basic training and experience standards, suggesting that teacher training and experience are considered important for promoting student learning. Since the passage of NCLB, several studies have evaluated the effect of teacher training and experience on student academic achievement, the results of which are inconclusive. Among first graders, Croninger et al. (2007) found a small negative effect of overall teacher education level (i.e., holding a master's degree or higher) within a school on student gains in math achievement; however, no statistically significant effects have been found for teacher education level on student gains in reading or math achievement among kindergartners (Guarino,

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Hamilton, Lockwood, Rathbun, & Hausken, 2006); second graders (Huang & Moon, 2009); or third through fifth graders (Clotfelter, Ladd, & Vigdor, 2007). Supplemental analyses completed by Croninger et al. suggest that the observed negative effect for overall teacher education level in a school may have been due to teachers not holding a degree in elementary education. With respect to experience, statistically significant positive effects for years teaching have been observed for student reading (Clotfelter et al., 2007; Huang & Moon, 2009) and math (Clotfelter et al., 2007) achievement; however, it should be noted that Croninger et al. (2007) and Guarino et al. (2006) did not find a statistically significant relationship between years teaching and student academic achievement.

  Beliefs and practices.

  Teacher efficacy. Teachers' sense of efficacy, or self-efficacy, refers to teachers' confidence in their skills and ability to influence student learning through instructional strategies, classroom management, and student engagement (Tschannen-Moran & Woolfolk Hoy, 2001). It is believed that teachers who are more efficacious are more likely to apply effective teaching practices that promote student learning. Indeed, statistically significant, positive relationships have been found between teacher efficacy and teachers' use of instructional practices that foster mastery goals in students (Wolters & Daugherty, 2007), and student scores on standards-based measures of math achievement (Hines & Kritsonis, 2010). Additionally, teacher efficacy for classroom management has been found to mediate the relationship between student race/ethnicity and teacher ratings of student behavior such that teachers with high efficacy show fewer differences between African American and Caucasian students on ratings of externalizing

behavior and social skills than do teachers with low efficacy (Peters et al., 2014).

Finally, statistically significant, positive relationships have been found between collective teacher efficacy, or the confidence that the unit of teachers within a school has the skills and ability to influence student learning (Tschannen-Moran & Barr, 2004), and school-level performance on norm-referenced measures of reading and math (Goddard, Hoy, & Woolfolk Hoy, 2000), standards-based measures of writing (Tschannen-Moran & Barr, 2004), and percent of students reaching mastery on standards-based measures of reading, writing, and math (McCoach & Colbert, 2010).

Collaboration. Teacher collaboration refers to the extent that teachers work with other school professionals to achieve a common goal. It is believed that when teachers work collaboratively, particularly around instruction, the shared knowledge, skills, and experiences enhance instructional practices, coordinate resources, and, in turn, improve student academic performance (Hart, 1998; Rosenholtz, 1989). Recently, empirical research has emerged that supports this hypothesized relationship between teacher collaboration and student academic achievement. For example, Goddard, Goddard, and Tschannen-Moran (2007) found a statistically significant, positive relationship between teacher collaboration at the aggregated school level and fourth grade students' performance on both norm-referenced and standards-based measures of reading and math. Similarly, Goddard, Miller, Larson, and Goddard (2010) found a statistically significant, positive effect of teacher collaboration at the aggregated school level and third grade students' performance on standards-based measures of reading and math.

Job satisfaction. Teacher job satisfaction refers to the extent that a teacher finds fulfillment and pleasure in their role as a teacher and in their daily activities working with

students and other school professionals. It is believed that job satisfaction can influence student performance indirectly through teachers' involvement, motivation, efficacy, and commitment to teaching. Indeed, teachers reporting low levels of job satisfaction are more likely to express low levels of commitment to their job and seem to have fewer coping strategies for addressing stressors in the work environment (McCarthy, Lambert, & Reiser, 2014). However, teachers who report high levels of job satisfaction feel more efficacious with respect to their classroom management skills and their ability to apply high-quality instructional practices (Klassen & Chiu, 2010). More importantly, Johnson, Kraft, and Papay (2012) found a direct, positive relationship between teacher job satisfaction and student academic achievement such that higher teacher satisfaction with working conditions was associated with higher gains on standards-based measures of reading and math at the aggregated school level.

Instructional practices. Instructional practices refer to the application of learning theories and teaching methods that guide student interactions and the delivery of instruction in the classroom. Several studies conducted within the elementary school setting have evaluated the effect of teachers' instructional practices on student academic achievement. Specifically, teachers' self-reported use of effective instructional practices have been positively associated with gains on criterion-referenced measures of reading (Guariano, Hamilton, Lockwood, & Rathbun, 2006; Palardy & Rumberger, 2008; Xue & Meisels, 2004) and math (Guariano et al., 2006; Palardy & Rumberger, 2008). The findings were similar across studies that directly observed teachers' instructional practices. Specifically, Firmender, Gavin, and McCoach (2014) found that actively engaging students in verbal dialogue about math and reinforcing the use of appropriate

math vocabulary was associated with gains on both norm-referenced and researcher-developed measures of math achievement. Additionally, Schacter, Thum, and Zifkin (2006) found a strong positive relationship between instructional practices that promote student creativity and gains on norm-referenced measures of reading, language arts, and math achievement.

Research on Predictors of Referral to Problem-Solving Teams

When identifying literature on predictors of student referrals to problem-solving teams, search terms included *referral* with *student, teacher,* and *team.* The search of the literature yielded only one study (Pas et al., 2010) that considered predictors of student referrals to problem-solving teams. Using multilevel modeling and a large sample population of elementary school students ($n = 9795$), teachers ($n = 491$), and schools ($n = 31$), Pas et al. (2010) evaluated the effect of teacher beliefs, or more specifically their level of burnout and efficacy, on three separate student outcomes: office discipline referrals, referrals to problem-solving teams, and referrals for special education. Results for predictors of student referrals to problem-solving teams are summarized in this section, and results for predictors of student referrals to special education will be reviewed in a later section.

Pas et al. (2010) included several characteristics of students, teachers, and schools in the analysis to control for their possible effects on student referral. Characteristics of students included sex, race/ethnicity, eligibility for FARM, and teacher ratings of both concentration and disruptive behavior problems. Teacher characteristics included the percentage of students in the class that the teacher referred, as well as sex, race/ethnicity, level of education, and years teaching. School characteristics included enrollment,

mobility rate, suspension rate, percentage of students receiving FARM, and average teacher ratings of their school's organizational health, or the level of collegiality, efficiency, and orderliness.

When evaluating the effect of student, teacher, and school characteristics on student referrals to problem-solving teams, Pas et al. (2010) considered both main and cross-level interaction effects using multilevel logistic regression to account for the nesting of students within teachers within schools. Results were not significant for any of the cross-level interactions considered; however, small to moderate main effects were found for student, teacher, and school characteristics. Student characteristics that statistically significantly predicted referral included sex, FARM, and concentration problems such that boys, students receiving FARM, and students whom teachers rated as presenting with concentration problems were more likely to be referred. Furthermore, as would be expected, students in classrooms with a high percentage of referrals were more likely to be referred. Teacher characteristics that statistically significantly predicted referral included sex and efficacy such that teachers who were male or low in efficacy were less likely to refer students. Only one of the school characteristics, suspension rates, statistically significantly predicted referral such that students in schools with high suspension rates were more likely to be referred. No statistically significant effects were found for student or teacher race/ethnicity, student disruptive behaviors, teacher education or experience, or teacher burnout. Additionally, no statistically significant effects were found for school enrollment, mobility rate, percent receiving FARM, or average teacher ratings of a school's organizational health.

As the only quantitative study on predictors of referral to problem-solving teams available in peer-reviewed journals within the past 20 years, Pas et al. (2010) provides valuable information about the possible relationships among characteristics of students, teachers, and schools, and the likelihood that a student will be referred. Findings suggest that student and teacher characteristics are more relevant than school characteristics for predicting referral. Specifically, student and teacher demographic characteristics, student behavior, and teacher beliefs, but not teacher experience, were found to statistically significantly predict referral.

However, the Pas et al. (2010) study is not without limitations. Although no effect was found for student or teacher race/ethnicity, only dichotomous indicators for Caucasian and African American were considered due the small sample of students and teachers from other ethnic groups. Therefore, the relationship between race/ethnicity and referral for other ethnic groups and within a more diverse sample population is unknown. Moreover, both student behavior and academic achievement are the primary reasons teachers provide as their basis for referral (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991); however, Pas et al. only considered the effect of behavior. Therefore, the relationship between student referral to problem-solving teams and characteristics of students and teachers when both student academic achievement and behavior are considered was not evaluated.

Research on Predictors of Referral to Special Education

When identifying literature on predictors of student referrals to special education, search terms included *referral* with *student, teacher,* and *special education.* The search of the literature on predictors of student referrals to special education yielded a total of

eight studies. Among the studies, two different methods for obtaining information about student referrals were observed, namely school records and simulated or scripted scenarios. In the sections that follow, the specific methods, measures, and findings from each study will be described. Studies that obtained referral data using school records will be discussed first followed by those that used scripted or simulated scenarios.

Data from school records. Three studies (Goodman & Webb, 2006; Pas et al., 2010; Wallingford & Prout, 2000) obtained information about student referrals to special education using school records. Identifying student referrals through school records has a fundamental advantage over using scripted or simulated scenarios. Specifically, identifying referred and non-referred students through school records provides researchers with the opportunity to evaluate predictors of referral within the naturalistic, real world context of schooling. However, researchers may not have the opportunity to systematically alter conditions or contexts, thereby limiting their ability to make causal inferences.

Using elementary school records from a single school district, Wallingford and Prout (2000) evaluated the effect of being young for grade due to having a summer birth date on student referrals. A series of chi square analyses were conducted across three different age groups in order to compare observed student referrals ($n = 1,222$) with expected referrals given the overall student population ($N = 16, 379$). Students in the 5- to 7-year-old group with a summer birth date were referred at a greater rate than would be expected by chance. Birth month was not significant for students in the older age groups.

Goodman and Webb (2006) evaluated the effect of student sex, race/ethnicity, and limited English proficiency (LEP) on student referrals for a suspected reading disability.

Data for third- and fourth-grade students were collected from a single school across a three-year period, and chi square analyses compared observed student referrals ($n = 66$) with expected referrals given the overall sample of third- and fourth-grade students ($N = 958$). Although student sex and race/ethnicity were not significant, students identified as LEP were referred at lower rates than would be expected by chance. According to Goodman and Webb, students identified as LEP received instruction in bilingual or other language supported classrooms, and the ability of this instructional model to meet the needs of LEP students may explain their lower than expected rates of referral.

When evaluating the effect of student, teacher, and school characteristics on student referrals to problem-solving teams, Pas et al. (2010) separately considered the effect of these characteristics on student referrals to special education using the same multilevel logistic regression model and sample population of elementary school students ($n = 9795$), teachers ($n = 491$), and schools ($n = 31$). Small to moderate main effects were found for student sex, race/ethnicity, FARM, concentration problems, disruptive behavior, and percentage of classroom students referred. Specifically, boys, students receiving FARM, students whom teachers rated as presenting with concentration problems, and students in classrooms with a high percentage of referrals were more likely to be referred; however, students who were African American and students whom teachers rated as presenting with disruptive behaviors were less likely to be referred. Instead, findings suggest that African American and disruptive students were more likely to be referred to the principal for disciplinary reasons. No statistically significant effects were found for teacher sex, race/ethnicity, education, experience, efficacy, or burnout. Additionally, no statistically significant effects were found for school enrollment,

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mobility rate, suspension rate, percent receiving FARM, or average teacher ratings of a school's organizational health.

Summary. Across studies that obtained information about teacher referrals for special education eligibility from school records (Goodman & Webb, 2006; Pas et al., 2010; Wallingford & Prout, 2000), a broad range of student, teacher, and school characteristics were considered. Findings suggest that student demographic characteristics, services being received, and behavior are more relevant than teacher or school characteristics for predicting referral. However, two of the studies (Goodman & Webb, 2006; Wallingford & Prout, 2000) did not evaluate the effect of teacher characteristics, considered only a narrow selection of student characteristics, and failed to consider the two primary reasons teachers provide as their basis for referral: student behavior and academic achievement (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991). Furthermore, findings in Goodman and Webb may not generalize to other schools, grade levels, or referral concerns given the specific model for delivering instruction to LEP students, as well as the focus on specific grade levels and reasons for referral. Pas et al. (2010) is the only study referencing school records that considered a broad range of student, teacher, and school characteristics, including student behavior; however, the effect of academic achievement was not evaluated

Data from the use of scripted or simulated scenarios. Five studies (Abidin & Robinson, 2002; Egyed & Short, 2006; Hill, Baldo, & D'Amato, 1999; Schwartz, Wolfe, & Cassar, 1997; Sciutto, Nolfi, & Bluhm, 2004) obtained information about student referrals using scripted or simulated scenarios. These studies asked teachers to make referral decisions after reviewing student vignettes or after considering a selected set of

students. One major advantage of using scripted or simulated scenarios when evaluating

student referral is the ability to conveniently and systematically alter conditions or

contexts, thereby establishing a foundation for drawing causal inference. However, even

a well-crafted scenario or simulation may not reflect the complexity of student

functioning within the classroom or the context in which teachers make referral

decisions. Therefore, findings from studies using scenarios reflect teacher decisions that

may meaningfully differ from their actual performance.

Three studies (Egyed & Short, 2006; Hill et al., 1999; Sciutto et al., 2004) asked

teachers to rate their likelihood of referring students described in researcher-drafted

vignettes. In Egyed and Short (2006), teachers ($N = 106$) completed questionnaires about

their training, years teaching, efficacy, and burnout, and reviewed a vignette describing a

disruptive eight-year-old male student. Results from separate ANOVA investigations of

the relationship between teacher characteristics and the likelihood of referral found no

statistically significant effects for efficacy, training, or teaching experience. However,

findings for burnout were statistically significant such that teachers with high burnout

were more likely to report uncertainty about their likelihood of referral.

Hill et al. (1999) asked teachers ($N = 84$), to complete self-report measures of

self-concept, tolerance, locus of control, and efficacy before reviewing hypothetical

records for three students who were struggling academically. The three students differed

with respect to their reported classroom behavior such that one student was acting out

with aggressive and defiant behavior, one student was exhibiting shy and withdrawn

behavior, and the remaining student was exhibiting neither acting out nor withdrawn

behavior. A discriminant analysis of the four teacher beliefs and referral decisions for the

three types of student behaviors was unable to identify any group differences, suggesting that teacher beliefs were not related to their referral decisions.

In Sciutto et al. (2004), teachers ($N = 199$) completed questionnaires about their sex, years teaching, knowledge of Attention Deficit Hyperactivity Disorder (ADHD), and number of previous referrals to special education due to concerns about ADHD symptoms. The teachers were randomly assigned one of six student vignettes that differed according to ADHD symptom type and student sex. In other words, the vignettes described either a male or a female student who presented with either inattentive, hyperactive, or both hyperactive and aggressive behavior in the classroom. Controlling for teacher ratings of the described child's perceived disruptiveness, results from an ANOVA investigation of sex and symptom type found an interaction effect such that boys were more likely to be referred across all symptom types, but statistically significant differences between boys and girls were only observed for the hyperactive condition. Additional analyses found no statistically significant effects for teacher sex, experience, or knowledge of ADHD.

The two remaining studies (Abidin & Robinson, 2002; Schwartz et al., 1997) that obtained information about student referrals using scripted or simulated scenarios attempted to introduce naturalistic student responses and classroom contexts. Abidin and Robinson (2002) asked teachers ($N = 30$) to select three students of the same sex and race/ethnicity from within their classrooms and rate the likelihood of referring the students for evaluation. Each of the three students was to match one of the following descriptions: frequently exhibits problem behaviors, occasionally exhibits problem behaviors, and rarely exhibits problem behaviors. Teachers completed questionnaires

about their level of teaching stress, and rating scales about behavior problems and academic competence for each of their three students. Additionally, researchers obtained student demographic information, including age, sex, race/ethnicity, and FARM eligibility, and completed classroom observations in order to obtain information about the percentage of observation intervals the selected students were off-task. Results using hierarchical multiple regression identified that observations of off-task behavior, teacher ratings of problem behaviors, and teacher ratings of academic competence statistically significantly accounted for 51% of the variance in ratings for the likelihood of student referral; however, no effects were found for student demographic characteristics or teacher stress.

Schwartz et al. (1997) asked a sample of experienced ($n = 27$) and pre-service ($n = 38$) teachers to complete self-report measures of self-esteem and locus of control before observing videotaped interviews of two different students. The students were of the same age, sex, and race/ethnicity; however, one of the students had previously been determined eligible for special education as a student with an emotional disability (ED). During the interview, the students described how they would respond to a set of proposed everyday moral, behavioral, and social dilemmas. After observing the interviews, teachers completed student behavior ratings and indicated their likelihood of referring each student. Results from multiple regression and path analyses identified that both experienced and pre-service teachers rated the student with ED as being in greater need of support, and that teachers were less likely to refer students demonstrating high impulse control. Additionally, pre-service teachers with an external locus of control and low self-

esteem were more likely to refer students, especially students who were rated as demonstrating low social judgment and low self-esteem.

Summary. Across the five studies that obtained information about student referrals using scripted or simulated scenarios (Abidin & Robinson, 2002; Egyed & Short, 2006; Hill et al., 1999; Schwartz et al., 1997; Sciutto et al., 2004), a broad range of student and teacher characteristics were considered, including student and teacher demographics, student behavior and academic competence, teacher experience, and teacher beliefs. However, each study only considered a narrow range of characteristics, and the effect of student academic performance on referral was evaluated in only one of the studies (Abidin & Robinson, 2002). Additionally, the findings across studies are inconclusive such that characteristics found to statistically significantly predict referral in some studies were not statistically significant in others. Small sample sizes (i.e., $N <$ 200) were a notable limitation across all five studies and may have restricted the ability to detect small to moderate effects. Furthermore, the inconclusive findings may reflect inherent problems with the authenticity and consistency of teachers' referral decisions based on scripted or simulated scenarios.

Summary of Reviewed Literature

Student academic achievement and behavior are the two primary reasons teachers provide as their basis for referring students to support services (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991). A review of the literature published in peer reviewed journals within the past 20 years revealed statistically significant relationships between student achievement or behavior, and characteristics of students and teachers. Statistically significant student characteristics included the demographic characteristics of

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sex (Lachance & Mazzocco, 2006; McIntosh et al., 2013; Miner & Clarke-Stewart, 2008; Peters et al., 2014; Scheiber et al., 2015), race/ethnicity (Downey & Pribesh, 2004; Hsin & Xie, 2014; Miner & Clarke-Stewart, 2008; Peters et al., 2014; Plata & Masten, 1998), and age (Crothers et al., 2010; Huang & Invernizzi, 2012; NICHD, 2007; Stipek & Byler, 2001); service eligibility for FARM (Burnett & Farkas, 2008; Dearing et al., 2006; Henninger & Luze, 2012; Kieffer, 2012; Peters et al., 2014), ESOL (Dawson & Williams, 2008; Han, 2010; Kieffer, 2008, 2011; Kieffer & Vukovic, 2013), and special education (Christ et al., 2010; Schulte & Stevens, 2015); and student-teacher relationship quality (Baker, 2006; Baker et al., 2008; Birch & Ladd, 1997; Fowler et al., 2008; McCormick & O'Connor, 2015). Statistically significant teacher characteristics included the demographic characteristics of sex (Taylor et al., 2001), race/ethnicity (Downey & Pribesh, 2008; Fowler et al., 2008; Pigott & Cowan, 2000), and age (Peters et al., 2014); education and experience (Clotfelter et al., 2007; Croninger et al., 2007; Huang & Moon, 2009); and beliefs and practices, such as teacher efficacy (Goddard et al., 2000; Hines & Kritsonis, 2010; McCoach & Colbert, 2010; Peters et al., 2014; Tschannen-Moran & Barr, 2004; Wolters & Daugherty, 2007), collaboration (Goddard et al., 2007, 2010), job satisfaction (Johnson et al., 2012), and instructional practices (Guariano et al., 2006; Firmender et al., 2004; Palardy & Rumberger, 2008; Schacter et al., 2006; Xue & Meisels, 2004).

Unfortunately, the available literature that has applied quantitative methods to identify predictors of student referrals to problem-solving teams is limited. In fact, a search of the literature revealed only one quantitative study (Pas et al., 2010) published in peer-reviewed journals within the past 20 years. Using multilevel modeling, Pas et al.

(2010) found small to moderate main effects for student sex, FARM eligibility, and concentration problems, as well as teacher sex and efficacy, on student referrals. No statistically significant main effects were found for student or teacher race/ethnicity, student disruptive behavior problems, teacher education level, or teacher experience. However, the primary focus of Pas et al. was on the effect of teacher efficacy and burnout on student referrals, and as such, only a few key student and teacher characteristics were included as covariate controls. Additionally, Pas et al. did not consider student academic achievement as a predictor, and race/ethnicity was limited to dichotomous indicators of Caucasian and African American. Therefore, the effect of student and teacher characteristics, including the effect of race/ethnicity other than Caucasian and African American, on student referral when both academic achievement and student behavior are considered is unknown.

Although students referred to problem-solving teams and special education are somewhat different sample populations, the available literature that has applied quantitative methods to identify predictors of student referrals to special education is more prevalent and provides information about factors relevant to the referral of struggling students. A search of the literature identified eight studies published in peer-reviewed journals within the past 20 years that applied quantitative methods to identify predictors of student referrals to special education. Three studies referenced naturally occurring, school data (Goodman & Webb, 2006; Pas et al., 2010; Wallingford & Prout, 2000), and five studies referenced scripted or simulated scenarios (Abidin & Robinson, 2002; Egyed & Short, 2006; Hill et al., 1999; Schwartz et al., 1997; Sciutto et al., 2004).

Among the studies that referenced school data, statistically significant effects were found for student sex, race/ethnicity, FARM eligibility, and behavior (Pas et al., 2010); being young for grade (Wallingford & Prout, 2000); and being identified as limited English proficient (Goodman & Webb, 2006) on student referrals to special education. However, both Goodman and Webb (2006) and Wallingford and Prout (2000) considered a narrow range of factors, and neither considered the effect of student academic achievement or behavior. Although Pas et al., (2010) included a broad range of factors, the effect of student academic achievement was not evaluated. Therefore, the effect of student and teacher characteristics on student referral to special education when both academic achievement and student behavior are considered is unknown.

Among the studies that referenced scripted or simulated scenarios, a broad range of student and teacher characteristics were considered; however, each study only considered a narrow range of characteristics, the role of both student academic achievement and behavior was considered in only one of the studies (Abidin & Robinson, 2002), and one study (Egyed & Shor, 2006) neither considered the role of student academic achievement nor behavior. Overall, two studies (Egyed & Short, 2006; Schwartz et al., 1997) found statistically significant effects of teacher beliefs, and one study (Sciutto et al., 2004) found statistically significant effects of student sex on student referrals to special education. The remaining two studies (Abidin & Robinson, 2002; Hill et al., 1999) found no statistically significant effects of student or teacher characteristics on student referrals to special education. However, the validity of inferences from these studies is limited due to their small sample size and reliance on hypothetical scenarios

that may not reflect the complexity of student functioning within the classroom or the

context in which teachers make referral decisions.

Chapter 3: Methods

Introduction

The purpose of this chapter is to describe the data and methods used to identify characteristics of students and teachers that predicted and differentiated student referrals to two problem-solving teams: Instructional Consultation Teams (IC Teams: Rosenfield & Gravois, 1996) and Child Study Teams (CS Teams: Moore et al., 1989). The first section describes the data source and collection procedures. The second section describes the participant sample. The third section describes the outcome and predictor measures. The fourth section describes the data analytic procedures.

Data Source

A four-year experimental evaluation of IC Teams conducted during the 2005-2006 through the 2008-2009 academic years (Rosenfield & Gottfredson, 2010) collected data annually from all 45 public elementary schools within a suburban county in the mid-Atlantic region of the United States. Of the 45 schools, 17 were randomly assigned to implement IC Teams, 17 were randomly assigned to control conditions, and 11 had been implementing IC Teams for one to three years prior to the experimental evaluation. All of the schools continued to implement the district's previously adopted intervention team model: CS Teams. Therefore, two different intervention team models, IC Teams and CS Teams, were concurrently operating in 28 of the schools.

The current study referenced archival data collected from the 28 schools that were implementing both IC Teams and CS Teams. Each school had been implementing CS Teams for several years prior to the introduction of IC Teams. According to Schien (1999), introducing new programs and procedures may disrupt or challenge the status quo, and resistance to this type of change is common. Furthermore, Frechtling (2007)

and Fullan (2001) have suggested that moderate levels of acceptance to change may take up to five years. Therefore, in order to maximize the potential for IC Teams to have reached a moderate level of acceptance within the schools, this study focused on predicting student referrals to the two teams during the 2008-2009 academic year, which was the final year of data collection and the year in which schools had been implementing both IC Teams and CS Teams for at least four years.

Data from the 2007-2008 and 2008-2009 academic years were obtained from records maintained on compact discs provided by one of the principal investigators in the experimental evaluation of IC Teams (Rosenfield & Gottfredson, 2010). During the experimental evaluation, data were collected from multiple sources. The school district submitted de-identified student rosters, student grades, and teacher rosters to the researchers at the end of each academic year. Researcher-developed surveys were administered to teachers online through the school district intranet in February of each academic year. Consenting teachers completed a Teacher Self-Report (TSR) about their beliefs and practices and a Teacher Report on Student Behavior (TRSB) for each student in their classroom. Finally, problem-solving team coordinators in each school maintained a Systems Tracking Form (STF), which the school district de-identified and submitted for all four years of data collection at the conclusion of the experimental evaluation.

Participant Sample

The participant sample was drawn from archival data that included all 17,124 kindergarten through fifth grade students and their 747classroom teachers within the 28 schools implementing IC Teams and CS Teams during the 2008-2009 academic year. However, kindergarten students ($N = 2883$) and their teachers ($N = 116$) were excluded

from the current study (referenced subsequently as the "excluded sample") because kindergartners were not enrolled during the previous academic year, and as such, several predictors were not measured and could not reasonably be imputed. Among the remaining first through fifth grade students and their classroom teachers, additional exclusions from the study were made for the following reasons: (a) the STFs necessary for identifying students who were referred to IC Teams and CS Teams during the 2008-2009 school year were not submitted for two of the schools, (b) teacher identification codes necessary for matching students with their classroom teachers were missing in the student rosters for 63 students, and (c) student rosters indicated that 12 teachers had only one student in their classroom, and a class size of one is insufficient for modeling within and between group variability, as was the aim for this study. Therefore, the final participant sample included first through fifth grade students ($N = 13,025$) and their classroom teachers ($N = 570$) within schools ($N = 26$) implementing both IC Teams and CS Teams during the 2008-2009 academic year. A summary of demographic characteristics, student services received, and teacher experience is provided in Table 1.

Table 1

Demographic Characteristics, Student Services Received, and Teacher Experience for Final Participant Sample

	Students (N = 13025)			Teachers (N = 570)	
Characteristic	n	%	Characteristic	n	%
Sex			Sex		
Female	6361	48.8	Female	512	91.6
Male	6664	51.2	Male	47	9.4
Race/Ethnicity			Race/Ethnicity		
Caucasian	4679	35.9	Caucasian	449	79.8
African American	2944	22.6	African American	71	12.6
Hispanic	3919	30.1	Hispanic	13	2.3
Asian/Pacific Is.	824	6.3	Asian/Pacific Is.	8	1.4
American Indian	28	0.2	American Indian	2	0.4
Unspecified/Other	631	4.8	Unspecified/Other	20	3.6
Young for Grade	985	7.6	Master's Degree	259	54.5
Old for Grade	1484	11.4	Years Teaching		
New to District	2266	17.4	1 year or less	24	5.1
Grade			2 to 5 years	145	30.9
First	2687	20.6	6 to 10 years	113	24.0
Second	2620	20.1	11 to 20 years	101	21.5
Third	2586	19.9	More than 20 years	87	18.5
Fourth	2602	20.0	Years at School		
Fifth	2530	19.4	1 year or less	65	13.9
Services[a]			2 to 5 years	244	52.2
Special Education	1590	12.2	6 to 10 years	85	18.2
FARM	5615	43.1	11 to 20 years	40	8.6
ESOL	3811	29.3	More than 20 years	33	7.1

Note. FARM = Free or reduced price meals. ESOL = English as a second or other language. Percentages are rounded to the nearest tenth and are valid percents to account for missing data.
[a]Services received during the 2008-09 academic year.

Chi-square tests of independence were conducted to determine if the demographic characteristics, student services received, and teacher experience differed between the included and excluded samples. When comparing the two samples, a per-comparison alpha of 0.05 was used, and because multiple chi-square analyses were performed, it was expected that 5% of the student ($n = 1$) and teacher ($n = 1$) measures would statistically significantly differ by chance alone. Indeed, differences between the two samples were found that exceeded the number of differences expected by chance alone. The proportion of students in the included sample was statistically significantly higher for the following

characteristics: Caucasian, African American, Asian/Pacific Islander, unspecified/other race/ethnicity, and fourth grade enrollment. The proportion of students in the excluded sample was statistically significantly higher for the following characteristics and services received: Hispanic, first grade enrollment, special education, free or reduced price meals, and English as a second or other language. The proportion of teachers with six to ten years of teaching experience was statistically significantly higher in the included sample, and the proportion of teachers with two to five years of teaching experience was statistically significantly higher in the excluded sample. Although statistically significant differences were found between the included and excluded samples, the sizes of the effects were small to negligible (i.e., $\varphi < .15$). Results from the chi-square analyses for the included and excluded samples of students and teachers are provided in Tables 2 and 3, respectively.

Table 2

Demographic and Services Differences Between Included and Excluded First through Fifth Grade Students

Characteristic	Included ($n = 13025$)		Excluded ($n = 1216$)			
	M	*SD*	*M*	*SD*	χ^2	φ
Sex (male)	.51	.50	.49	.50	2.38	-.013
Race						
Caucasian	.36	.48	.32	.47	6.30	-.021 *
African American	.23	.42	.17	.37	20.70	-.038 ***
Hispanic	.30	.46	.43	.49	81.15	.075 ***
Asian/Pacific Islander	.06	.24	.05	.21	5.15	-.019 *
American Indian	.00	.05	.00	.05	.05	.002
Unspecified/Other	.05	.21	.03	.18	6.65	-.022 **
Young for Grade	.08	.26	.07	.25	1.30	-.010
Old for Grade	.11	.32	.14	.35	9.71	.026 **
New to District	.17	.38	.19	.39	1.24	.009
Grade						
First	.21	.40	.24	.43	8.07	.024 **
Second	.20	.40	.21	.41	.61	.007
Third	.20	.40	.20	.40	.03	-.001
Fourth	.20	.40	.17	.37	8.36	-.024 **
Fifth	.19	.40	.19	.39	.41	-.005
Services[a]						
Special Education	.12	.33	.14	.35	4.18	.017 *
FARM	.43	.49	.50	.50	19.47	.037 ***
ESOL	.29	.45	.40	.49	66.18	.068 ***

Note. FARM = Free or reduced price meals. ESOL = English as a second or other language. All measures are dichotomous with 0 = No, 1 = Yes, and the mean indicates the proportion of students for each measure. Chi-square *df* = 1. Effect size, φ, is calculated as the square root of χ^2/N.

[a]Services received during the 2008-09 academic year.

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

Table 3

Demographic and Experience Differences Between Included and Excluded First Through Fifth Grade Classroom Teachers

Characteristic	Included (N = 570)		Excluded (N = 61)		χ^2	φ
	M	SD	M	SD		
Sex (male)	.08	.28	.07	.26	.16	-.016
Race						
Caucasian	.80	.40	.83	.38	.30	.022
African American	.13	.33	.09	.28	.78	-.035
Hispanic	.02	.15	.03	.18	.29	.022
Asian/Pacific Islander	.01	.12	.00	.00	.83	-.037
American Indian	.00	.06	.02	.13	2.05	.057
Unspecified/Other	.04	.18	.03	.18	.00	-.002
Masters Degree or Higher	.55	.50	.59	.50	.40	.027
Teaching Experience						
1 year or less	.05	.22	.04	.20	.08	-.012
2 to 5 years	.31	.46	.50	.50	7.26	.118 **
6 to 10 years	.24	.43	.10	.31	4.60	-.094 *
11 to 20 years	.21	.41	.13	.33	2.15	-.064
More than 20 years	.19	.39	.23	.42	.55	.033
Years at School						
1 year or less	.14	.35	.22	.42	2.57	.071
2 to 5 years	.52	.50	.51	.50	.03	-.007
6 to 10 years	.18	.39	.12	.33	1.08	-.046
11 to 20 years	.09	.28	.08	.28	.01	-.004
More than 20 years	.07	.26	.06	.24	.06	-.011

Note. All measures are dichotomous with 0 = No, 1 = Yes, and the mean indicates the proportion of students for each measure. Chi-square df = 1. Effect size, φ, is calculated as the square root of χ^2/N.

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

Measures

This study sought to identify predictors of student referrals to IC Teams and CS Teams during the 2008-2009 academic year. The outcome measure was the indicator of student problem-solving team referral status. Predictors included student and teacher demographic characteristics, student services being received, student academic achievement, prior student behavior ratings, prior student-teacher relationship ratings, teacher experience, and teacher ratings of their beliefs and practices. As cited in the literature review, these measures have previously been associated with the two primary

reasons provided by teachers as their basis for making student referrals, namely student academic achievement and behavior (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991), or they have been considered in previous research on student referrals to problem solving teams and special education.

Measures were obtained using data collected during the 2007-2008 and 2008-2009 academic years. When predicting student referral, the outcome measure and demographic characteristics were obtained using data from the 2008-2009 academic year. Characteristics of students and teachers that were situational or likely to differ before and after referral, perhaps due to the referral itself, such as academic achievement, were obtained using data from the 2007-2008 academic year or the first quarter of 2008-2009 to ensure temporal precedence of the predictors. Unless otherwise specified, all continuous variables were standardized (i.e., mean = 0 and standard deviation = 1) and categorical variables were dummy coded (i.e., no = 0 and yes = 1) to facilitate interpretability of the results. A list of measures included in this study is provided in Table 4. A more detailed description of the measures follows, and a summary of the measures, their data source, and coding scheme is provided in Appendix I.

Table 4

Measures Included in the Current Study

Outcome	Predictors	
	Student	Teacher
Student Referral	Demographics	Demographics
	Sex	Sex
	Race/Ethnicity	Race/Ethnicity
	Young for Grade	Age in Years
	Old for Grade	Experience
	New to District	Master's Degree or Higher
	Services Received	Years Teaching
	Special Education	Years at School
	FARM	Beliefs and Practices
	ESOL	Efficacy
	Academic Achievement	Collaboration
	Reading	Job Satisfaction
	Writing	Instructional Practices
	Math	
	Behavior	
	Concentration	
	Externalizing	
	Internalizing	
	Student-Teacher Relationship	
	Closeness	
	Conflict	

Note. FARM = Free and reduced price meals. ESOL = English as a second or other language.

Student-level outcomes. The outcome measure for this study was an indicator of student problem-solving team referral during the 2008-2009 academic year. Referred students and the problem-solving team to which they were referred were ascertained by the presence of their de-identified student roster code on a systems tracking form (STF), which team coordinators used to document relevant case information for the purposes of ongoing case management. Examples of the STFs for IC Teams and CS Teams are provided in Appendices J and K, respectively.

When referring a student, teachers self-selected to receive support from the IC Team or the CS Team. Although it was possible for students to have been referred to both teams during the school year, in this study, each referred student was served through either the IC Team or CS Team, but not both. As such, the outcome measure had three

mutually exclusive levels: referral to IC Teams, referral to CS Teams, or not referred. The outcome measure was coded as IC Teams = 1, CS Teams = 2, and not referred = 3. This categorical coding scheme was necessary for the statistical analytic procedures used in this study, and it rendered 'not referred' the referent group.

Student-level predictors.

Demographics. Student demographic characteristics for sex, race/ethnicity, young for grade, and old for grade for were obtained using data from the 2008-2009 student rosters. Student sex was dummy coded with female as the referent group. The school district categorized student race/ethnicity as follows: Caucasian, African American, Asian, Hawaiian, American Indian/Alaskan Native, and Unspecified/Other. The categories for Asian and Hawaiian were combined into Asian/Pacific Islander in order to correspond with categories the district used for teachers. Additionally, given the small sample of students identified as American Indian/Alaskan Native (i.e., fewer than 0.5%), this category was combined with Unspecified/Other when predicting student referral. The resulting race/ethnicity categories were dummy coded with Caucasian as the referent group. Young for grade and old for grade were derived by first subtracting student date of birth from September 30, 2008, which was the cut-off date for the minimum age of kindergarten entry according to state and district criteria. Student age was then compared with grade level age expectations given a minimum allowable age of 5 years upon entry to kindergarten. Students whose age did not reach expectations were identified as young for grade, and students whose age exceeded expectations by more than one year were identified as old for grade.

Although not previously identified as a factor in the literature on student

achievement, behavior, and referrals to problem-solving teams or special education, a

measure of whether a student was new to the district was included in this study. Given

that the scope and sequence of academic curricula can differ between school systems, it

was hypothesized that students who were new to the district may present with academic

skill deficits for which teachers might make a problem-solving team referral. The

measure of being new to the district was obtained by comparing data from the 2007-2008

and 2008-2009 student rosters. Students who were new to the district were identified by

the absence of their de-identified student code in the 2007-2008 student roster.

Services. Services being received included eligibility, monitoring, or up to two

years post-monitoring for English as a second or other language (ESOL) instruction;

eligibility to receive free and reduced price meals (FARM); and eligibility for special

education. Both ESOL and FARM were considered proxy measures for student

demographic characteristics, namely primary language and family income, respectively,

and were measured using the 2008-2009 student rosters. Eligibility for special education,

however, may have changed during the 2008-2009 academic year, and in some cases,

may have depended on referral to either the IC Team or CS Team. Therefore, eligibility

for special education was measured using the 2007-2008 student rosters.

Achievement. Academic achievement was measured using teacher-assigned first

quarter grades in the academic content areas of reading, writing, and math as indicated in

district-provided 2008-2009 grades. Although teacher-assigned grades are not objective

measures of achievement, they are common indicators of academic achievement and

progress used by schools and parents. The district used different marking rubrics across

grade levels such that first through second grade students were assigned grades ranging from "N" (not meeting expectations) to "S+" (outstanding), and third through fifth grade students were assigned grades ranging from "F" (failure) to "A" (outstanding). Grades were recoded from nominal to numerical values in the following manner: S+ or A = 4; B+ = 3.4; S or B = 3; C+ = 2.4; S- or C = 2; D+ = 1.4; N or D = 1; and F = 0. Finally, each content area grade was standardized within their respective rubric.

Behavior. Student behavior was measured using ratings from the 2007-2008 Teacher Report on Student Behavior (TRSB), a survey on which teachers rated individual student behavior and student-teacher relationship quality. Therefore, student behavior was rated by each student's previous teacher, and the measures derived from this survey indicated a student's prior behavior rating. Across all four years of data collection during the experimental evaluation of IC Teams (Rosenfield & Gottfredson, 2010), response rates for the TRSB were high and ranged from 85% to 94% (Vu, 2012). The TRSB measured behavior using three scales: Concentration, Externalizing, and Internalizing. A summary of the items that composed each of the three TRSB behavior scales is provided in Appendix L.

The Concentration, Externalizing, and Internalizing scales included items that were adapted from the Teacher Observation of Classroom Adaptation, Revised (TOCA-R; Werthamer-Larsson, Kellam, & Wheeler, 1991) and were rated using a four point Likert-scale (i.e., *Never/Almost Never = 0, Sometimes = 1, Often = 2,* and *Very Often = 3*). The Concentration scale included eight items and measured student attention and diligence to task. The Externalizing scale included eight items and measured disruptive, defiant, or other acting out behaviors. The Internalizing scale included eight items and

measured shy, anxious, or withdrawn behaviors. Mean composites for each of the three

scales were derived, and standardized composite scores were used when predicting

student referral. Alpha reliabilities for the mean composites were high and were as

follows: Concentration ($\alpha = .92$), Externalizing ($\alpha = .90$), and Internalizing ($\alpha = .84$).

     Student-teacher relationship. Student-teacher relationship quality was measured

using ratings from the 2007-2008 TRSB. Therefore, the student-teacher relationship was

rated by each student's previous teacher, and the measures derived from this survey

indicated a student's relationship with their previous teacher. The TRSB included two

scales pertaining to student-teacher relationship quality: Closeness and Conflict. A

summary of the items that composed each of the two TRSB student-teacher relationship

scales is provided in Appendix M.

     The Closeness and Conflict scales included items that were adapted from the

Student-Teacher Relationship Scale (STRS; Pianta, 2001) and were rated using a five

point Likert-scale (i.e., *Definitely Does Not Apply = 0, Not Really = 1, Neutral, Not Sure

= 2, Applies Somewhat = 3,* and *Definitely Applies = 4*). The Closeness scale included

four items and measured the degree to which the child and teacher shared a caring,

supportive relationship. The Conflict scale included four items and measured the degree

to which the child and teacher shared a contentious or unpredictable relationship. Mean

composites for the two scales were derived, and standardized composite scores were used

when predicting student referral. Alpha reliabilities for the mean composites were high

and were as follows: Closeness ($\alpha = .85$) and Conflict ($\alpha = .86$).

Teacher-level predictors.

Demographics. Teacher demographic characteristics of sex, race/ethnicity, and age in years were obtained using data from the 2008-2009 teacher rosters. Sex was dummy coded with female as the referent group. The school district categorized teacher race/ethnicity as follows: Caucasian, African American, Hispanic, Asian/Pacific Islander, American Indian/Alaskan Native, and Unspecified/Other. Given the large sample of Caucasian teachers (i.e., 79.8%) and the relatively small sample of teachers from each of the remaining race/ethnicity categories (see Table 1), a dichotomous dummy variable was derived for teacher race/ethnicity when predicting student referral with Caucasian as the referent group. Age in years was a continuous measure derived by subtracting teacher date of birth from September 2, 2008, or the first day of the 2008-2009 school year.

Experience. Teacher experience included education level, years teaching, and years teaching at the current school, which were measured using the 2008-2009 Teacher Self Report (TSR): a survey of individual teacher experiences, beliefs, and practices. Across all four years of data collection during the experimental evaluation of IC Teams (Rosenfield & Gottfredson, 2010), response rates for the TSR were high and ranged from 84% to 89% (Vu et al., 2013). The TSR measured education level using the following categories: Bachelor's degree, Bachelor's degree and additional coursework, Master's degree, Master's degree and additional coursework, and Doctorate. When predicting student referral, these categories were recoded to yield a dichotomous dummy variable indicating whether the teacher possessed a master's degree or higher versus a bachelor's degree. Years teaching and years teaching at the current school were measured using the following categories: 1 year or less, 2-5 years, 6-10 years, 11-20 years, and more than 20

years. When predicting student referral, these categories were recoded into 1 to 5 years, 6 to 10 years, and 11 or more years to reflect beginning, intermediate, and advanced levels of experience. Beginning levels of experience, or 1 to 5 years, was the referent group.

Beliefs and practices. Teacher beliefs and practices were measured using responses on the 2007-2008 TSR survey. Therefore, the measures derived from this survey indicated a teacher's prior beliefs and practices. The TSR included four scales pertaining to teacher beliefs and practices: Teacher Efficacy, Instructional Practices, Collaboration, and Job Satisfaction. As was previously stated, across all four years of data collection during the experimental evaluation of IC Teams (Rosenfield & Gottfredson, 2010), response rates for the TSR were high and ranged from 84% to 89% (Vu et al., 2013). A summary of the items that composed each of the four TSR scales is provided in Appendix N.

The Teacher Efficacy scale included 16 items that were adapted from the Teachers' Sense of Efficacy Scale, Efficacy for Instructional Strategies (ISES EIS; Tschannen-Moran & Hoy, 2001; Tschannen-Moran, Hoy, & Hoy, 1998). The scale measured teacher beliefs in their ability to adapt to and support students with learning and behavioral challenges, and it was rated using a five point Likert-scale (i.e., *Nothing/Not At All = 1, Very Little = 2, Some = 3, Quite a Bit = 4,* and *A Great Deal = 5*).

The Collaboration and Instructional Practices scales were developed by the researchers conducting the experimental evaluation of IC Teams (Rosenfield & Gottfredson, 2010). The Collaboration scale included 10 items and measured perceptions that school staff coordinates with and supports each other. The Instructional Practices

scale included 18 items and measured the application of effective instructional principles and practices. For both scales, items were rated using a five point Likert-scale (i.e., *Never = 1, Rarely = 2, Sometimes = 3, Often = 4,* and *Always = 5*).

The Job Satisfaction scale included four items that were adapted from Bryk and Schneider (2002). The scale measured teacher loyalty and appreciation for the school, and it was rated using a five point Likert-scale (i.e., *Strongly Disagree = 1, Disagree = 2, Neutral = 3, Agree = 4,* and *Strongly Agree = 5*).

Mean composites for each of the four scales were derived, and standardized composite scores were used when predicting student referral. Alpha reliabilities for the mean composites were high and were as follows: Teacher Efficacy ($\alpha = .92$), Collaboration ($\alpha = .80$), Instructional Practices ($\alpha = .90$), and Job Satisfaction ($\alpha = .91$).

Data Analysis

Introduction. Data in this study were hierarchical such that students were nested within teachers within schools. Given the nested structure of the data, predictors of student referral to IC Teams and CS Teams were identified using multilevel modeling and the Hierarchical Linear Modeling program (HLM 7.01: Raudenbush et al., 2011). HLM simultaneously partials out total variance in the dependent variable into within and between-group variance, thereby providing the opportunity to disaggregate individual, group, and cross-level interaction effects. Before conducting the multilevel data analysis, the influence of missing data and potential multicollinearity was explored and addressed.

Missing data. Data are missing when observed measures do not have values for one or more cases. The prevalence of missing data within the participant sample was explored using the Analyze Patterns module in IBM SPSS Statistics 22.0 for Windows.

Results from the exploration indicate that almost all measures had missing data, and data were missing for approximately one third of the students and two fifths of the teachers. However, only about one fifth of all possible values were missing, suggesting that the overall amount of missing information, or the number of missing values in the data matrix, was relatively small. A summary of the prevalence of missing data is provided in Table 5.

Table 5

Percentage of Missing Data for Students and Teachers

Participant	Measures	Cases	Values
Students	83.7	32.4	18.0
Teachers	100.0	42.1	23.5

Note. Measures include the individual survey items. Cases are individual students and teachers. Values are the units of data across measures and within cases.

Rubin (1976) and colleagues (Little & Rubin, 2002) have described three mechanisms by which data may be missing: missing completely at random, missing at random, and missing not at random. When data are missing completely at random (MCAR), the probability of missing data for any given variable is unrelated to the value of that variable or the value of any other variables in the analysis. When data are missing at random (MAR), the probability of missing data for a given variable is unrelated to the value of that variable, but may be related to other variables in the analysis. When data are missing not at random (MNAR), the probability of missing data for a given variable is related to the value of that variable, even after controlling for systematic relationships with other variables in the analysis.

For several measures in this study, the probability of missing data was known to be related to other measures in the analysis. Specifically, TRSB composites and special education eligibility data were missing for students who were new to the district.

Similarly, TSR composites were missing for teachers who were not employed the previous academic year such that they had one year or less teaching experience or years working at the current school. Therefore, the data in this study were not MCAR. While it is possible that data in this study were MAR, testing that assumption was not possible because missing values were unobserved, and the relationship between missingness and the value of a given variable was unknowable (Allison, 2000; Enders, 2010a; Shafer & Graham, 2002).

Most statistical methods and software packages, including multilevel modeling and the HLM program (Raudenbush et al., 2011), assume complete sample case data. Listwise deletion, single imputation, and multiple imputation are three methods for addressing missing data that are compatible with HLM. Listwise deletion excludes all cases and units with incomplete data from the analysis. Single imputation makes use of available data to replace missing values with estimates, thereby generating a complete data set that can be used for further analysis. Multiple imputation, proposed by Rubin (1987), generates $m > 1$ imputed data sets with different estimated values, and results are pooled, or averaged, across each of the m sets when conducting statistical analyses.

Listwise deletion and single imputation have several disadvantages that are overcome with multiple imputation (Allison, 2000; Enders, 2010a; Shafer & Graham, 2002); therefore, multiple imputation was the method for handling missing data in this study. First, listwise deletion assumes that data are MCAR, and when data are not MCAR, as was the case for this study, listwise deletion can produce biased parameter estimates. Moreover, when the percentage of cases with missing data is moderate to large, as was the case for this study, listwise deletion substantially reduces the effective

sample size, thereby reducing statistical power and inflating standard errors. Although sample size is retained with single imputation, most single imputation methods produce biased parameter estimates even when data are MCAR. Furthermore, all methods of single imputation underestimate sampling error, which increases the risk of Type 1 error. However, multiple imputation introduces random variance into the estimated values, and when data are MAR, pooling results across the $m > 1$ data sets yields relatively unbiased parameter estimates. Furthermore, multiple imputation is fairly robust to violations of MAR when the fraction of missing information is small (Raudenbush & Bryk, 2002). In this study, the fraction of missing information, or unexplained variation in the missing data, may have been small due to the known relationship between several included measures and the probability of missingness.

Procedures. Missing data were imputed using the Multiple Imputation module in IBM SPSS Statistics 22.0 for Windows, which uses an iterative Markov Chain Monte Carlo (MCMC) algorithm in order to simulate random draws from a distribution of missing values (IBM Corporation, 2011). Linear regression is used to impute missing values for continuous variables, and logistic regression is used to impute missing values for categorical variables. During each MCMC iteration, and for each imputed variable, missing values are predicted using known values for variables included in the multiple imputation model. Therefore, the validity of imputed values depends highly on the variables included in the model.

When generating a multiple imputation model, three recommended guidelines help to ensure that the imputed values make use of and preserve features inherent in the natural data structure (Allison, 2000; Enders, 2010a; Shafer & Graham, 2002). First,

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dependent and independent measures of interest in the analysis should be included as predictors. When possible, auxiliary variables, or measures that correlate with missingness or missing values, should be included as predictors in order to strengthen the assumption of MAR, increase statistical power, and reduce non-response bias. Finally, higher order relationships of interest in the analysis, such as interaction effects, should be included so that the magnitudes of the effects are not attenuated when conducting the analysis.

In accordance with the recommended guidelines (Allison, 2000; Enders, 2010a; Shafer & Graham, 2002), the imputation model for this study included as predictors the dependent and independent measures of interest in the analysis. Imputed continuous measures were constrained within allowable maximum and minimum values, the TRSB and TSR scales were imputed at the item level, and multi-category measures, such as race/ethnicity and teaching experience, were imputed using district assigned categories before they were recoded for use in the analysis. Auxiliary variables included the following 2008-2009 counterparts to predictors measured during 2007-2008: special education services, content area grades, TRSB composites, and TSR composites. These measures were chosen as auxiliary variables because measures of the same construct taken at two different points in time are likely correlated. Summaries of the measures included in the models for multiply imputing missing student and teacher data are provided in Tables 6 and 7, respectively.

Table 6

Measures Included in the Multiple Imputation of Students Model

Imputed and Predictors	Auxiliary Predictors	
Student	Student	Teacher
Demographics	Services Received	Demographics
Sex	Special Education[a]	Sex
Race	IC Team	Race
Young for Grade	CS Team	Age
Old for Grade	Academic Achievement[d]	Experience
New to District	Reading	Master's or Higher
Services Received	Writing	Years Teaching
Free/Reduced Meals	Math	Years at School
English as Second Language	Behavior[a, e]	Beliefs and Practices[a, e]
Special Education[a]	Concentration	Efficacy
Academic Achievement[b]	Externalizing	Collaboration
Reading	Internalizing	Job Satisfaction
Writing	Closeness	Instructional Practices
Math	Conflict	
Behavior[a, c]		
Concentration		
Externalizing		
Internalizing		
Student-Teacher Relationship[a, c]		
Closeness		
Conflict		

[a]Measured during the previous 2007-08 school year. [b]Measured during the first quarter of the 2008-09 school year. [c]Individual survey items for each composite were imputed. [d]Mean composites of second through fourth quarter grades. [e]Mean composites of survey items.

Table 7

Measures Included in the Multiple Imputation of Teachers Model

Imputed and Predictors	Auxiliary Predictors	
Teacher	Student[c]	Teacher
Demographics	Demographics	Beliefs and Practices[a, e]
Sex	Sex	Efficacy
Race	Race	Collaboration
Age	Young for Grade	Job Satisfaction
Experience	Old for Grade	Instructional Practices
Master's or Higher	New to District	
Years Teaching	Services Received	
Years at School	Free/Reduced Meals	
Beliefs and Practices[a, b]	English as Second Language	
Efficacy	Special Education[a]	
Collaboration	IC Team	
Job Satisfaction	CS Team	
Instructional Practices	Academic Achievement[d]	
	Reading	
	Writing	
	Math	
	Behavior[a, e]	
	Concentration	
	Externalizing	
	Internalizing	
	Student-Teacher Relationship[a, e]	
	Closeness	
	Conflict	

[a]Measured during the previous 2007-08 school year. [b]Individual survey items for each composite were imputed. [c]Aggregated by teacher across multiply imputed sets of student-level data. [d]Measured during the first quarter of the 2008-09 school year. [e]Mean composites of survey items.

Although the data structure was nested and cross level interactions were of interest in this study, proposed algorithms for imputing multilevel data (Goldstein, Carpenter, & Browne, 2014; Shin & Raudenbush, 2011; Yucel, 2008) require specialized software and are not yet included in standard statistical analysis packages, including IBM SPSS Statistics (Yucel, 2011). Failing to account for nesting violates the assumption of independence that underlies the linear and logistic regression methods used to impute the missing values, and it yields underestimated standard errors (Luke, 2004; Raudenbush & Bryk, 2002). However, Zhang (2005) demonstrated through a Monte Carlo study that

failing to account for nesting by using a flat file when multiply imputing data may be inconsequential when the level of missing data is less than 30%, as was the case in this study

In addition to possible statistical complications associated with using a flat file to impute nested data, an important functional complication can arise. Specifically, higher level units may be assigned different imputed values on a given variable within an imputed set. For example, missing data for teacher sex could be imputed as "female" across some of the student cases and as "male" for others, thereby yielding a nonsensical or ambiguous aggregated indicator for teacher sex in the teacher-level file used for multilevel modeling. Therefore, Gelman and Hill (2007) and Petrin (2006) recommend multiply imputing data separately for each level of nesting and including imputed values from each level when imputing subsequent levels.

Given the limitations of IBM SPSS Statistics 22.0 for accommodating nested data structures when multiply imputing missing data, the data in this study were imputed using a flat file. However, in accordance with guidelines for avoiding functional complications associated with using a flat file to impute nested data (Gelman & Hill, 2007; Petrin, 2006), student- and teacher-level data were imputed separately. Student-level data was imputed first with disaggregated teacher measures to be used in the analysis included as auxiliary variables. When imputing teacher-level data, student measures, which included the indicator of referral and measures to be used in the analysis, were aggregated across the $m > 1$ imputations and included as auxiliary variables. While not fully accounting for nesting, imputing data separately for each level of nesting and including measures from different units as auxiliary variables makes use of the data structure, as is consistent with

guidelines for generating a multiple imputation model (Allison, 2000; Enders, 2010a;

Shafer & Graham, 2002). The data imputation process model used in this study is

depicted graphically below in Figure 1.
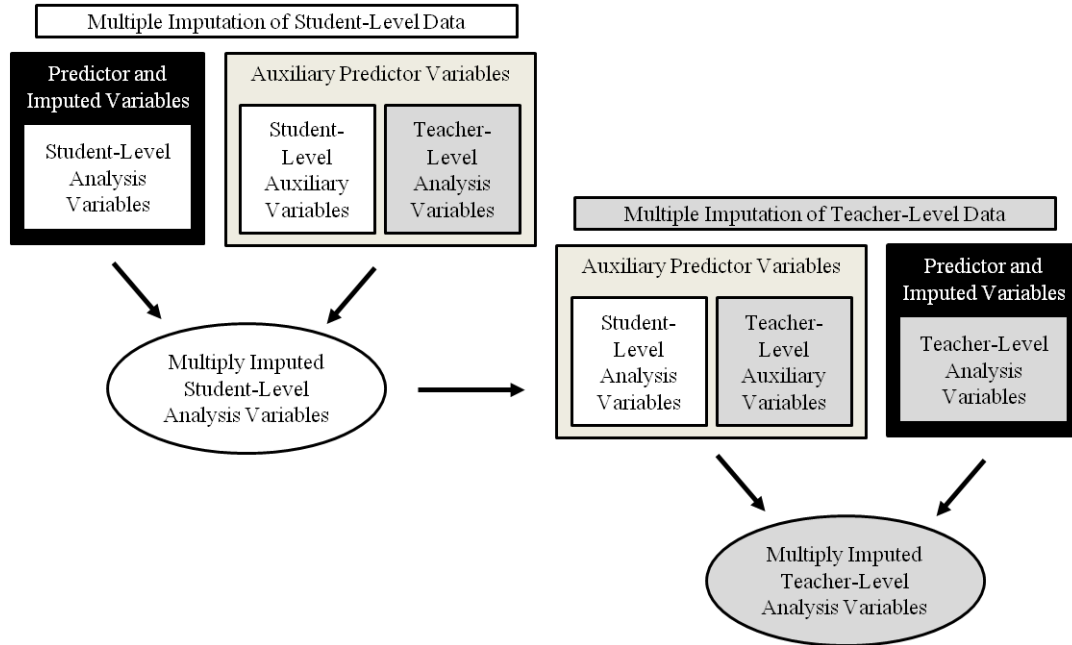
Figure 1. Process model for the multiple imputation of missing student- and teacher-level data.

Two additional considerations when conducting multiple imputation include the

number of imputations and the number of iterations between imputations. According to

Rubin (1987), the efficiency of a multiple imputation standard error relative to a

theoretical minimum is defined as

$$RE = \left(1 + \frac{FMI}{m}\right)^{-1} \tag{1}$$

where *m* is the number of imputations and FMI is the fraction of missing information.

For example, with 30% missing information, relative efficiency with $m = 10$ imputations

is $100/(1 + .03) = 97\%$. According to Enders (2010a), more than 10 imputations has a

negligible added effect on relative efficiency. However, Graham, Olchowski, and

Gilreath (2007) found that more than 10 imputations appreciably increases statistical

power, but more than 20 imputations is unnecessary unless the fraction of missing

information is high (i.e., FMI > .50). Given that the greatest percentage of missing values

in this study was 23.5% (see Table 2), and the percent of missing values may somewhat

overestimate the fraction of missing information since variables included in the

imputation model are correlated with missingness or the value of imputed variables, 20

imputed data sets would be ideal for maximizing both relative efficiency and statistical

power. However, HLM 7.01 (Raudenbush et al., 2011) is limited to handling 10 imputed

data sets. Therefore, 10 imputed data sets were generated when multiply imputing the

student- and teacher-level data for this study.

As previously stated, the Multiple Imputation module in SPSS uses an iterative

MCMC algorithm, which is a two-step procedure that includes an imputation step (I-step)

and a posterior step (P-step) that is then repeated iteratively (IBM Corporation, 2011).

While the I-step generates an imputed set of missing values, the P-step uses the imputed

values from the preceding I-step in order to estimate the mean vectors and covariance

matrices from which imputed estimates are drawn in the next I-step. Therefore, the I-

steps and P-steps are dependent, and the imputed values from successive iterations are

correlated. Using correlated imputed data sets can negatively bias standard errors during

the analysis phase (Enders, 2010a). However, after a set number of iterations, k, the

distributions from which imputed values are drawn between t and $t + k$ iterations

converge, or are no longer dependent.

Assessing for convergence is important for identifying the number of iterations to

separate each multiply imputed data set and for increasing the likelihood that the imputed

sets are uncorrelated. Currently there are no definitive tests of convergence. However, Enders (2010b) developed a diagnostic macro for use with SPSS that provides useful information to assess convergence. Following a sample imputation of two multiply imputed data sets with 1000 iterations separating the sets, the macro graphically depicts the potential scale reduction factors (PSR), or ratios of variances within and between the I- and P-step chains, for every 100 iterations. Convergence is estimated as the least number of iterations for which the PSR < 1.05 and begins to stabilize in magnitude.

Sample imputations with two multiply imputed data sets and 1000 iterations separating the sets were conducted for the student- and teacher-level data. Following the sample imputations, the diagnostic macro (Enders, 2010b) was performed for both the student- and teacher-level data. A review of the PSR graphs for the student- and teacher-level sample imputations indicated that the PSR < 1.05 and began to stabilize at 500 iterations. Therefore, it was determined that 500 iterations would separate the imputed sets of data when multiply imputing the student- and teacher-level files. The PSR graphs for the student- and teacher-level sample imputations are provided in Figures 2 and 3, respectively.
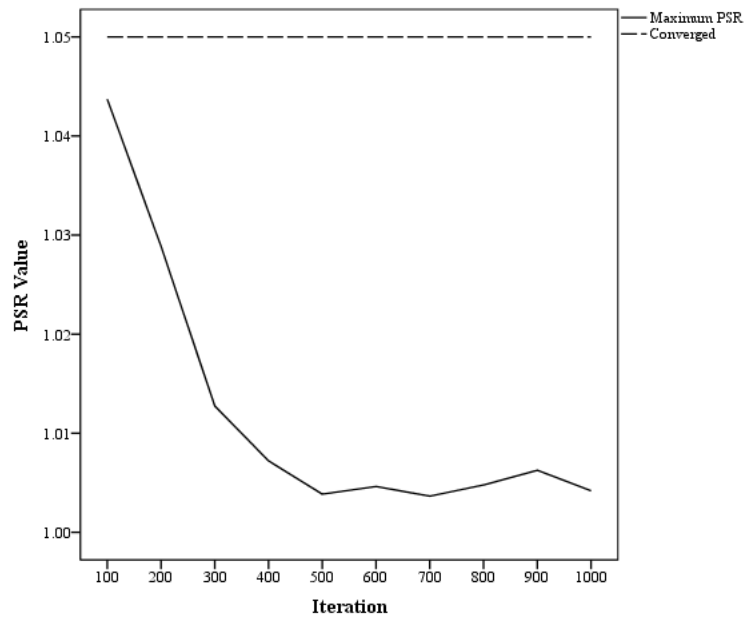
Figure 2. Graph generated by the diagnostic macro (Enders, 2010b) indicating the Potential Scale Reduction Factor (PSR) for every 100 iterations following the sample multiple imputation of student-level data.
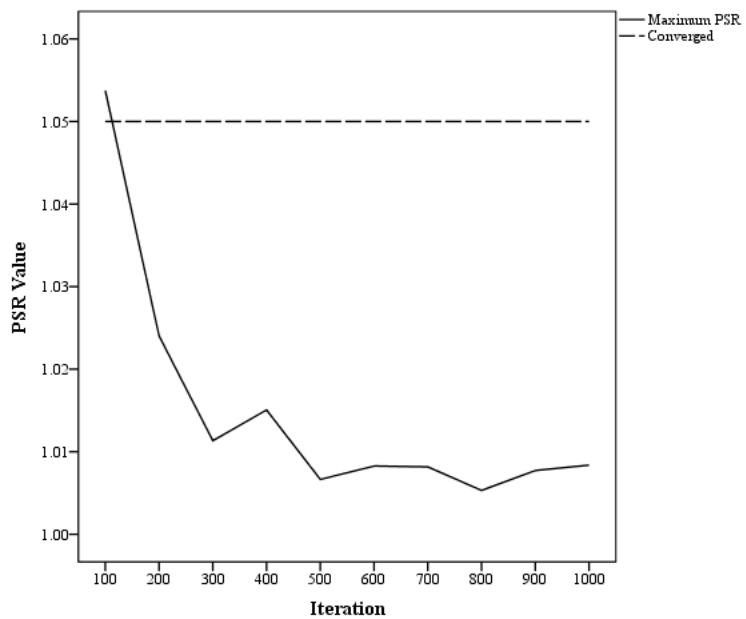
Figure 3. Graph generated by the diagnostic macro (Enders, 2010b) indicating the maximum Potential Scale Reduction Factor (PSR) for every 100 iterations following the sample multiple imputation of teacher-level data.

Multicollinearity. Multicollinearity occurs when two or more variables covary. Including collinear variables in regression analyses inflates standard errors and reduces statistical power, which complicates model specification by rendering the magnitude and direction of parameter estimates sensitive to changes in the model and by increasing the probability of Type II error (Pedhazur, 1997). Before predicting referral, multicolinearity within the student- and teacher-level measures was explored using SPSS Statistics 22.0 for Windows. Through an iterative approach, each student-level measure was entered into a multiple regression equation as a dependent variable with the remaining student-level measures as the independent variables. This iterative approach was repeated for the teacher measures. Multicolinearity diagnostics, specifically the variance inflation factor (VIF) and tolerance were evaluated. A tolerance less than .10, or a VIF greater than 10, indicates that more than 90% of the variance in one variable is shared with another, and this criterion was considered the maximum threshold (Cohen, Cohen, West, & Aiken, 2003). For the each of the student and teacher measures, the VIF and tolerance were within threshold limits. The bivariate correlations among the student- and teacher-level measures are provided in Tables 8 and 9, respectively.

Table 8

Correlations Among Student-Level Predictors

	Predictor	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Sex (male)	-	-.01	-.04*	.09*	.01	.01	.01	.10*	-.12*	-.16*	-.05*	-.19*	.13*	.06*	-.15*	.14*
2	Race		-	.04*	.01	.02*	.31*	.45*	-.04*	-.11*	-.08*	-.09*	-.03*	.00	.05*	-.05*	.00
3	Young for Grade			-	-.10*	.01	-.02*	.00	-.03*	.01	.00	-.02	-.02*	.00	.01	.01	.01
4	Old for Grade				-	.05*	.11*	.09*	.15*	-.12*	-.12*	-.12*	-.16*	.08*	.10*	-.08*	.06*
5	New to District					-	.03*	-.02	.00	-.09*	-.08*	-.09*	-.29*	.36*	.45*	-.27*	.36*
6	FARM						-	.45*	.01	-.28*	-.24*	-.25*	-.17*	.09*	.10*	-.09*	.07*
7	ESOL							-	-.03*	-.19*	-.17*	-.15*	-.06*	-.06*	.06*	-.03*	-.07*
8	Special Education								-	-.08*	-.11*	-.09*	-.17*	.04*	.11*	-.04*	.05*
9	Reading									-	.65*	.57*	.41*	-.20*	-.18*	.14*	-.19*
10	Writing										-	.56*	.43*	-.21*	-.20*	.14*	-.19*
11	Math											-	.41*	-.21*	-.19*	.13*	-.19*
12	Concentration												-	-.55*	-.51*	.43*	-.58*
13	Externalizing													-	.30*	-.30*	.79*
14	Internalizing														-	-.51*	.38*
15	Closeness															-	-.41*
16	Conflict																-

Note. FARM = Free or reduced price meals. ESOL = English as a second or other language.

p < .05.

Table 9

Correlations Among Teacher-Level Predictors

Predictor	1	2	3	4	5	6	7	8	9	10
1 Sex (male)	-	.05	-.02	.00	-.06	.00	-.08	-.12*	-.04	-.10*
2 Race (non-white)		-	-.06	.02	-.01	.03	-.14*	-.10	-.13*	-.07
3 Age			-	.12*	.61*	.41*	.08	.14*	.14*	.10*
4 Master's Degree or Higher				-	.10	.07	.02	.04	.02	-.02
5 Teaching Experience					-	.40*	.18*	.20*	.15*	.11*
6 School Experience						-	.07	.06	.11*	.09
7 Efficacy							-	.46*	.37*	.61*
8 Collaboration								-	.64*	.41*
9 Job Satisfaction									-	.26*
10 Instructional Practices										-

*p < .05.

Multilevel modeling. The outcome measure for this study, student problem-solving team referral during the 2008-2009 academic year, had three mutually exclusive levels: referral to IC Teams, referral to CS Teams, and not referred to a problem-solving team. Therefore, predictors of student referral to the two problem-solving teams were identified using a multinomial hierarchical general linear model (HGLM), which extends the Bernoulli model to more than two possible outcomes and uses the following logit link function:

$$\eta_{mij} = \log\left(\frac{\phi_{mij}}{\phi_{Mij}}\right) \tag{2}$$

where

$$\phi_{Mij} = 1 - \sum_{m=1}^{M-1} \phi_{mij} \tag{3}$$

such that η_{mij} is the log odds of person i in group j being in the m-th category relative to the M-th category, or the referent group, and ϕ_{mij} is the probability that person i in group j will be in category m for categories $m = 1, ..., M$, (M categories). For M categories, there are $(M - 1)$ sets of equations with membership in category m relative to *category M* identified as $0 =$ No, $1 =$ Yes, which allows predictors to differently associate with the

probability of participation for the different groups. In the current study, not being referred to a problem-solving team was the referent group, M or Category 3, and the following fully conditional model was used to identify predictors of referral to IC Teams (Category 1) relative to not being referred (Category 3) and CS Teams (Category 2) relative to not being referred (Category 3):

Level 1: $\eta_{ijk(m)} = \pi_{0jk(m)} + \sum_{p=1}^{P_m} \pi_{pjk(m)} a_{pijk}$ (4)

Level 3: $\beta_{00k(m)} = \gamma_{000(m)} + u_{00k(m)}$ (6)

$\beta_{0qk(m)} = \gamma_{0q0(m)} + u_{0qk(m)}$

$\beta_{p0k(m)} = \gamma_{p00(m)} + u_{p0k(m)}$

$\beta_{pqk(m)} = \gamma_{pqo(m)} + u_{pqk(m)}$

where

$i = 1, 2 ..,n_{jk}$ children within classroom j in school k;

$j = 1, 2, ...J_k$ classrooms within school k; and $k = 1, 2, ...K$ schools, and

$\eta_{ijk(m)}$ is the log odds of being referred to team m,

$\pi_{0jk(m)}$ is the mean log odds of referral to m in classroom j and school k,

$\pi_{pjk(m)}$ is the effect of a_{pijk} on the log odds of referral to m in classroom j and school k,

a_{pijk} is the level-1 predictor, or student variable, p,

$\beta_{00k(m)}$ is the mean log odds referral to m in school k,

$\beta_{0qk(m)}$ is the effect of X_{qjk} on the log odds of referral to m in school k,

X_{qjk} is the level-2 predictor, or teacher variable, s,

$\beta_{p0k(m)}$ is the mean effect of a_{pijk} on the log odds of referral to m in school k,

$\beta_{pqk(m)}$ is the effect of X_{qjk} on the relationship between a_{pijk} and the log odds of referral to m in school k,

$\gamma_{000(m)}$ is the grand mean log odds of referral to m across schools,

$\gamma_{0q0(m)}$ is the mean effect of X_{qjk} on the log odds of referral to m across schools,

$\gamma_{p00(m)}$ is the mean effect of a_{pijk} on the log odds of referral to m across schools,

$\gamma_{pq0(m)}$ is the mean effect of X_{qjk} on the relationship between a_{pijk} and the log odds of referral to m across schools , and

$r_{0jk(m)}, r_{pjk(m)}, u_{00k(m)}, u_{0pk(m)}, u_{p0k(m)},$ and $u_{pqk(m)}$ are residual error terms for referral to team m.

Model development. The multinomial HGLM model was built with student predictors at level-1 and teacher predictors at level-2, but no school predictors at level-3. Although level-3 does not have any school predictors, it was included to account for level-2 error variance, or differences across schools for mean classroom referrals and the effect of student and teacher characteristics on referral. Following recommendations in Raudenbush and Bryk (2002) and Luke (2004), the model was built incrementally in three stages. At the conclusion of the three model building stages, a fully conditional model is specified.

The first stage considered an unconditional model that included the outcome measure (i.e., student referral) in the absence of predictors. The purpose of beginning with an unconditional model was to calculate intraclass correlations (ICC) and determine if multilevel modeling was necessary. The ICC is a ratio that indicates the proportion of total variance in an outcome measure that is due to differences between groups, or in this study, the proportion of total variance in student problem-solving team referral that is due

to differences between classrooms and schools. According to Snijders and Bosker (2012), the ICC for a two-level model using a logit link function is calculated as follows:

$$\text{ICC} = \frac{\tau}{\tau + \frac{\pi^2}{3}} \tag{7}$$

where τ is the between group variance. Therefore, it follows that for a three-level model using a logit link function, such as the model in the current study, the ICC at each level of nesting would be calculated by substituting τ in the numerator with either τ_π or τ_β, and the following equation in the denominator:

$$\tau_\pi + \tau_\beta + \frac{\pi^2}{3} \tag{8}$$

where τ_π is the variance between level-two units, and τ_β is the variance between level-3 units. This modified equation was used to calculate the ICC at the teacher- and school-level for both IC Teams (Category 1) and CS Teams (Category 2).

The second stage focused on building the level-1 model. Student predictors were entered stepwise in blocks (i.e., demographics, services, achievement, and behavior), group-mean centered, with slopes free to vary across level-2 and level-3. Group-mean centering the predictors removes between-group variation, thereby providing truer estimates of pooled within-group regression coefficients and slope variance (Enders & Tofighi, 2007). After entering each block, decisions were made about retaining measures in the model and the homogeneity of level-1 slopes using the following five decision rules: (a) measures that predicted referral and varied across teachers and schools were retained as they were entered; (b) measures that predicted referral but only varied across teachers or schools were retained, group-mean centered, with the slope fixed at the level of non-significance and the remaining slope free to vary; (c) measures that predicted

referral, but did not vary across teachers or schools were retained, grand-mean centered with their slopes fixed; (d) measures that did not predict referral, but varied across teachers or schools were retained, grand-mean centered with their slopes fixed in order to more precisely account for between-group variation; and (e) measures that neither predicted referral nor varied across teachers or schools at were removed from the model. Furthermore, a liberal significance level of $p \leq .10$ was chosen when making decisions about retaining measures and evaluating homogeneity of level-1 slopes in order to decrease the chance of excluding predictors and slope variance that contributed to model fit.

The third stage focused on building the level-2 model. The intercept was built first, followed by any varying level-1 slopes. The process for building the level-2 model mirrored the process for building the level-1 model such that teacher measures were entered stepwise in blocks (i.e., demographics, experience, and beliefs and practices), group-mean centered, with their slopes free to vary. After entering each block, decisions were made about retaining measures and the homogeneity of level-2 slopes using similar decision rules and the significance level of $p \leq .10$ as was used when building the level-1 model. Specifically, measures that predicted referral and varied across schools were retained as they were entered. Measures that predicted referral, but did not vary across schools were retained, grand-mean centered with their slopes fixed. Measures that did not predict referral, but varied across schools were retained, grand-mean centered with their slopes fixed in order to more precisely account for between-group variation. Measures that neither predicted referral nor varied across schools were removed from the model.

Although multinomial HGLM calculates (M-1) sets of equations for M categories in order to allow predictors to differentially associate with the probability of participation across categories, there is only one underlying model with multiple outcomes being fitted. Therefore, when building multilevel models within a multinomial framework, decisions about centering, varying slopes, and removing measures are made jointly and in parallel across categories. In other words, a measure was removed because it neither statistically significantly predicted referral nor varied across teachers or schools for either Category 1 (IC Teams) or Category 2 (CS Teams). However, a measure was retained if it statistically significantly predicted referral or varied across teachers or schools for at least one of the problem-solving teams. Similarly, a slope was fixed because it did not statistically significantly vary across teachers or schools for either IC Teams or CS Teams. However, a slope that statistically significantly varied for at least one of the problem-solving teams was allowed to vary.

Coefficient contrasts. The multinomial HGLM identified predictors of student referral to each problem-solving team relative to not being referred. After specifying the fully conditional model, the retained measures were further evaluated using the multivariate hypothesis testing feature in HLM 7.01 (Raudenbush et al., 2011) in order to determine if there were statistically significant differences in the predictors of student referral to the two problem-solving teams relative to each other. For each measure, the pair of IC Teams (Category 1) and CS Teams (Category 2) coefficients from the multinomial HGLM were contrasted using a Wald test, and the results were evaluated for significance at $p \leq .05$. After the analysis, the magnitudes of the effects were determined

by calculating a relative odds ratio for each pair of measures, m, as follows:

$$\exp\left(\text{coefficient}_{m(1)} - \text{coefficient}_{m(2)}\right).$$

Chapter 4: Results

Introduction

The purpose of this chapter is to present results from the methods used to identify and differentiate the student and teacher characteristics that predicted student referrals to IC Teams and CS Teams. The first section presents summary descriptive statistics for the student and teacher measures. The second section presents the main findings from the multinomial HGLM analysis used to identify the predictors of student referrals. Within this second section, the findings from the unconditional model will be presented first followed by the findings from the fully conditional model. The third section presents findings from the multivariate hypothesis testing used to determine if the predictors for IC Teams and CS Teams statistically significantly differed between the two teams.

Descriptive Statistics

Across schools, problem-solving team use was prevalent among teachers; however, very few students were served through the problem-solving team process. Specifically, approximately 70% of teachers made referrals to IC Teams, CS Teams, or both, but only 6.5% of students were referred to a problem-solving team. Teacher team use and student referrals were relatively uniform across the two problem-solving team models. Approximately 45% of teachers made referrals to IC Teams, and approximately 50% made referrals to CS Teams. Among students, approximately 3% of students were referred to IC Teams, and approximately 3% of students were referred to CS Teams. A summary of student problem-solving team referrals and teacher team use is provided in Table 10.

Table 10

Student Problem-Solving Team Referrals and Teacher Team Use

Referral Status	Students		Teachers	
	n	%	*n*	%
No Referral	12171	93.4	164	28.8
IC Team Only	431	3.3	132	23.2
CS Team Only	423	3.2	147	25.8
IC Team & CS Team	0.0	0.0	127	22.3

Note. Percentages may not sum to 100 due to rounding.

Following the multiple imputation of missing student- and teacher-level data,

summary statistics (i.e., mean, standard deviation, minimum and maximum values, and

composite reliability) were obtained for each of the measures to be used in the

multinomial HGLM analysis. These summary statistics are presented in Tables 11 and

12 for the student- and teacher-level predictors, respectively. When obtaining summary

statistics from a multiple imputation data file, IBM SPSS Statistics 22.0 pools the means

across the imputed sets, but not the standard deviations, minimum and maximum values,

or composite reliabilities. As a result, summary statistics for the standard deviations,

minimum and maximum values, and composite reliabilities were obtained by reviewing

and comparing the results between each imputation. Across imputations, the standard

deviations and reliabilities slightly varied for each imputed measure, but the range

between minimum and maximum values did not exceed 0.05. Therefore, only one value,

the maximum value observed across imputations, is reported for each measure.

Table 11

Descriptive Statistics for Student-Level Predictors Following the Multiple Imputation of Missing Data

Measure	M	SD	Min	Max	Reliability
Demographics					
Sex (male)	.51	.50	0	1	
Race					
Caucasian	.36	.48	0	1	
African American	.23	.42	0	1	
Hispanic	.30	.46	0	1	
Asian/Pacific Is.	.06	.24	0	1	
Unspecified/Other	.05	.22	0	1	
Age					
Young for Grade	.08	.26	0	1	
Old for Grade	.11	.32	0	1	
New to District	.17	.38	0	1	
Services Received					
FARM	.43	.49	0	1	
ESOL	.29	.45	0	1	
Special Education[a]	.10	.31	0	1	
Academic Achievement[b]					
Reading	0	1	-3.92	1.52	
Writing	0	1	-4.13	1.70	
Math	0	1	-4.33	1.55	
Behavior[c]					
Concentration	0	1	-2.80	1.52	.92
Externalizing	0	1	-0.87	5.10	.91
Internalizing	0	1	-1.29	4.33	.87
Student-Teacher Relationship[c]					
Closeness	0	1	-4.46	1.11	.85
Conflict	0	1	-0.80	3.64	.88

Note. M = mean pooled across imputations. SD = maximum standard deviation across imputations. Min = minimum value across imputations. Max = maximum value across imputations. Reliability = maximum alpha reliability across imputations. FARM = Free or reduced price meals. ESOL = English as a second or other language. Demographic and service measures are coded 0 = No, 1 = Yes. Achievement and behavior measures are standardized.

[a]Special Education received in 2007-2008 . [b]First quarter grades in 2008-2009. [c]Mean composite scores from the 2007-2008 Teacher Report on Student Behavior survey.

Table 12

Descriptive Statistics for Teacher-Level Predictors Following the Multiple Imputation of Missing Data

Measure	M	SD	Min	Max	Reliability
Demographics					
Sex (male)	.09	.30	0	1	
Race (non-Causasian)	.21	.41	0	1	
Age in Years	0	1	-1.48	2.62	
Experience					
Master's Degree or Higher	.54	.50	0	1	
Years Teaching					
6 to 10 years	.21	.43	0	1	
11 or more years	.39	.49	0	1	
Years at School					
6 to 10 years	.17	.41	0	1	
11 or more years	.22	.43	0	1	
Beliefs and Practices[a]					
Efficacy	0	1	-3.44	2.31	.93
Collaboration	0	1	-3.68	1.99	.83
Job Satisfacation	0	1	-3.84	1.13	.92
Instructional Practices	0	1	-2.87	2.45	.90

Note. M = mean pooled across imputations. SD = maximum standard deviation across imputations. Min = minimum value across imputations. Max = maximum value across imputations. Reliability = maximum alpha reliability across imputations. All demographic and experience measures are coded as 0 = No, 1 = Yes. Age as well as beliefs and practices are standardized.
[a]Mean composite scores from the 2007-2008 Teacher Self Report survey.

Multinomial HGLM

Unconditional model. Results from the unconditional model indicate that between-group differences were present for both IC Teams and CS Teams. Overall, 15.4% of the total variance in student referrals to IC Teams relative to not being referred to a problem-solving team was due to between-group differences, and 9.7% of the total variance in student referrals to CS Teams relative to not being referred to a problem-solving team was due to between-group differences. Although the percentage of total variance due to between-group differences was small for both IC Teams and CS Teams, the findings discussed below regarding the statistical significance of the intraclass correlations (ICC) indicate an appreciable design effect warranting multilevel modeling.

With respect to IC Teams, the ICC between teachers was .108, and between schools was .046, indicating that, 10.8% of the total variance in student referrals to IC Teams was between teachers, and 4.6% was between schools. Additionally, using the liberal significance level of $p \leq .10$ for evaluating homogeneity of level-1 and level-2 slopes during the model building process, the average log odds of referral statistically significantly varied between teachers at $p = .065$, and between schools at $p < .001$. Results from the unconditional model for IC Teams are summarized in Table 13.

Table 13

Fixed and Random Effects for the Unconditional Model Predicting Student Referral to Instructional Consultation Teams Relative to Not Being Referred to a Problem-Solving Team

Fixed Effect	Coefficient	Standard Error	Odds Ratio	CI	p-value
Intercept, $\gamma_{000(1)}$	-3.441	0.098	.032	(.026, .039)	<.001

Random Effect	Standard Deviation	Variance Component	df	χ^2	p-value
Intercept, $r_{0(1)}$	.61076	.37302	544	594.670	.065
Intercept, $u_{00(1)}$	.40181	.16145	25	82.529	<.001

Note. CI = 95% confidence interval for the odds ratio.

With respect to CS Teams, the ICC between teachers was .038, and between schools was .059, indicating that 3.8% of the total variance in student referrals to CS Teams was between teachers, and 5.9% was between schools. Although the average log odds of referral did not statistically significantly vary between teachers such that $p > .500$, it did statistically significantly vary between schools at $p < .001$. Results from the unconditional model for CS Teams are summarized in Table 14.

Table 14

Fixed and Random Effects for the Unconditional Model Predicting Student Referral to
Child Study Teams Relative to Not Being Referred to a Problem-Solving Team

Fixed Effect	Coefficient	Standard Error	Odds Ratio	CI	p-value
Intercept, $\gamma_{000(2)}$	-3.447	0.108	.032	(.026, .040)	<.001

Random Effect	Standard Deviation	Variance Component	df	χ^2	p-value
Intercept, $r_{0(2)}$	.37312	.13922	570	531.957	>.500
Intercept, $u_{00(2)}$	.46758	.21863	26	104.132	<.001

Note. CI = 95% confidence interval for the odds ratio.

Fully conditional model. Among the 19 student- and 12 teacher-level variables

entered into the fully conditional model, all but 4 of the student- and 6 of the teacher-

level variables were retained using the liberal significance level of $p \leq .10$ during the

model building process. The following student-level variables did not contribute to

model fit and were dropped from the analysis: young for grade, old for grade, receiving

FARM, and prior externalizing behavior. The following teacher-level variables did not

contribute to model fit and were dropped from the analysis: Caucasian versus non-

Caucasian teacher race/ethnicity, 6 to 10 years of total teaching experience, and prior

teacher efficacy, collaboration, job satisfaction, and instructional practices. The results

are presented as odds ratios (OR), which indicate a ratio of the odds for one event relative

to the odds for another event. The relationship between the odds of an event and the

probability of an event is expressed as

$$\text{odds} = \frac{P}{1 - P} \tag{9}$$

with P as the probability of the event occurring, and $1 - P$ as the probability of the event

not occurring (Pedhazur, 1997). In other words, an OR of 1.0 indicates that two events

have the same odds, an OR > 1.0 indicates that there is an increase in odds for one event

relative to the other, and an OR < 1.0 indicates that there is a decrease in odds for one event relative to the other.

Question 1: Student-level predictors. Results from the fully conditional model indicate that several measures of student demographic characteristics, services received, academic achievement, prior behavior, and relationship quality with the prior teacher statistically significantly predicted student referral relative to not being referred to a problem-solving team above and beyond the effects of all other measures included in the model at $p \leq .05$ for both IC Teams and CS Teams.

With respect to referral to IC Teams relative to not being referred to a problem-solving team, the odds of referral were 26% higher for male students than for female students (odds ratio [OR] = 1.257, $p = .050$). Compared with Caucasian race/ethnicity, the odds of referral were 53% and 63% lower for Hispanic and Asian/Pacific Islander race/ethnicity, respectively (OR = 0.475, $p < .001$; OR = 0.383, $p = .013$). For students who were new to the district or received special education services the prior school year, the odds of referral were 34% and 37% lower than for returning or general education students, respectively (OR = 0.664, $p = .009$; OR = 0.628, $p = .014$). Regarding measures of academic achievement, one standard deviation increases in first quarter grades for reading, writing, and math were associated with 38%, 33%, and 34% reductions in the odds of referral, respectively (OR = 0.624, $p < .001$; OR = 0.668, $p < .001$; OR = 0.661, $p < .001$). Finally, a one standard deviation increase in prior behavior ratings for concentration was associated with a 37% reduction in the odds of referral (OR = 0.631, $p < .001$), and for relationship quality with the prior teacher, one standard deviation increases in closeness and conflict were associated with 35% and 26% increases in the

odds of referral, respectively (OR = 1.346, $p < .001$; OR = 1.262, $p < .001$). Being a

student for whom English is a second language, African American and Unspecified/Other

race/ethnicity, and prior behavior ratings for internalizing problems did not statistically

significantly predict student referral to IC Teams. Results from the fully conditional

model for IC Teams are summarized in Table 15.

Table 15

Fixed and Random Effects for the Fully Conditional Model Predicting Student Referral to Instructional Consultation Teams Relative to Not Being Referred to a Problem-Solving Team

Fixed Effect	Coefficient	Standard Error	Odds Ratio	CI	p-value
Intercept, $\gamma_{000(1)}$	-4.368	.141	.013	(.009, .017)	<.001
Teacher Measures					
Sex (male)	-.012	.227	.988	(.632, 1.545)	.959
Age	-.079	.094	.924	(.768, 1.111)	.398
Master's or Higher	-.159	.151	.853	(.633, 1.149)	.294
Teaching 11 years +	-.022	.202	.978	(.656, 1.458)	.912
At school 6 to 10 years	-.390	.225	.677	(.435, 1.056)	.085
At school 11 years +	-.671	.313	.511	(.268, .975)	.042
Student Measures					
Sex (male)	.229	.116	1.257	(1.000, 1.579)	.050
African American	.213	.148	1.238	(.925, 1.657)	.151
Hispanic	-.745	.226	.475	(.305, .740)	<.001
Asian/Pacific Islander	-.960	.388	.383	(.179, .818)	.013
Unspecified/Other	.279	.246	1.322	(.816, 2.141)	.256
New to District	-.409	.157	.664	(.488, .905)	.009
ESOL	.381	.202	1.463	(.985, 2.172)	.059
Special Education	-.465	.188	.628	(.434, .909)	.014
Reading	-.472	.070	.624	(.544, .716)	<.001
Writing	-.404	.095	.668	(.550, .811)	<.001
Math	-.414	.063	.661	(.585, .748)	<.001
Concentration	-.460	.101	.631	(.512, .777)	<.001
Internalzing	.119	.073	1.268	(.976, 1.301)	.103
Closeness	.297	.070	1.346	(1.173, 1.544)	<.001
Conflict	.233	.063	1.262	(1.114, 1.430)	<.001

Random Effect	Standard Deviation	Variance Component	df	χ^2	p-value
Intercept, $r_{0(1)}$	.74403	.55358	376	587.69588	<.001
Intercept, $u_{00(1)}$	.50476	.25478	23	62.27149	<.001
At school 11 years +	.69189	.47871	23	33.43775	.074
Writing	.30604	.09366	23	54.01012	<.001
Concentration	.19564	.03827	23	32.71451	.086

Note. CI = 95% confidence interval for the odds ratio. ESOL = English as a second or other language.

Many of the same student characteristics that predicted referral to IC Teams also predicted referral to CS Teams; however, there were some distinctions with the measures and their magnitudes. With respect to referral to CS Teams relative to not being referred to a problem-solving team, the odds of referral for male students was 36% higher than for female students (OR = 1.364, p = .005). Compared with Caucasian race/ethnicity, the odds of referral were 33%, 42%, and 43% lower for African American, Hispanic, and Unspecified/Other race/ethnicity, respectively (OR = 0.674, p = .006; OR = 0.585, p = .007; OR = 0.567, p = .041). Regarding measures of academic achievement, one standard deviation increases in first quarter grades for reading, writing, and math were associated with 23%, 33%, and 28% reductions in the odds of referral, respectively (OR = 0.767, p < .001; OR = .0670, p < .001; OR = 0.725, p < .001). Regarding prior teacher ratings of behavior, a one standard deviation increase in concentration was associated with a 26% decrease in the odds of referral (OR = 0.736, p = .005), and a one standard deviation increase in internalizing problems was associated with a 30% increase in the odds of referral (OR = 1.300, p < .001). Finally, with respect to relationship quality with the prior teacher, a one standard deviation increase in closeness was associated with a 22% increase in the odds of referral (OR = 1.222, p = .003). Asian/Pacific Islander race/ethnicity, being new to the district, being a student for whom English is a second language, receiving special education the previous academic year, and prior teacher ratings of conflict in the student-teacher relationship did not statistically significantly predict student referral to CS Teams relative to no referral. Results from the fully conditional model for CS Teams are summarized in Table 16.

Table 16

Fixed and Random Effects for the Fully Conditional Model Predicting Student Referral to Child Study Teams Relative to Not Being Referred to a Problem-Solving Team

Fixed Effect	Coefficient	Standard Error	Odds Ratio	CI	p-value
Intercept, $\gamma_{000(2)}$	-3.978	.133	.019	(.014, .025)	<.001
Teacher Measures					
Sex (male)	-.611	.261	.543	(.324, .908)	.020
Age	.196	.083	1.216	(1.033, 1.432)	.019
Masters or Higher	.086	.128	1.090	(.848, 1.401)	.502
Teaching 11 years +	-.355	.171	.701	(.501, .982)	.039
At school 6 to 10 years	-.158	.189	.854	(.587, 1.242)	.406
At school 11 years +	-.035	.235	.966	(.595, 1.567)	.883
Student Measures					
Sex (male)	.310	.111	1.364	(1.097, 1.696)	.005
African American	-.394	.142	.674	(.501, .891)	.006
Hispanic	-.536	.200	.585	(.395, .866)	.007
Asian/Pacific Islander	-.411	.280	.663	(.383, 1.147)	.141
Unspecified/Other	-.567	.278	.567	(.329, .978)	.041
New to District	-.151	.141	.860	(.652, 1.135)	.287
ESOL	-.253	.190	.776	(.535, 1.127)	.182
Special Education	-.157	.168	.855	(.614, 1.189)	.351
Reading	-.265	.069	.767	(.670, .879)	<.001
Writing	-.401	.080	.670	(.568, .790)	<.001
Math	-.321	.061	.725	(.643, .818)	<.001
Concentration	-.307	.099	.736	(.600, .902)	.005
Internalzing	.262	.067	1.300	(1.139, 1.484)	<.001
Closeness	.200	.066	1.222	(1.072, 1.393)	.003
Conflict	.118	.063	1.125	(.994, 1.273)	.061

Random Effect	Standard Deviation	Variance Component	df	χ^2	p-value
Intercept, $r_{0(2)}$	.42447	.18018	376	486.51803	<.001
Intercept, $u_{00(2)}$	.53753	.28893	23	73.46699	<.001
At school 11 years +	.39512	.15612	23	24.95721	.352
Writing	.15053	.02266	23	25.22937	.338
Concentration	.26213	.06871	23	40.04797	.015

Note. CI = 95% confidence interval for the odds ratio. ESOL = English as a second or other language.

Question 2: Teacher-level predictors. Results from the fully conditional model indicate that only a few teacher demographic and experience characteristics statistically significantly predicted student referral relative to not being referred to a problem-solving team above and beyond the effects of all other measures included in the model at $p \leq .05$ for IC Teams and CS Teams. With respect to referral to IC Teams relative to not being

referred to a problem-solving team (see Table 15), the odds of referral were 49% lower for students who had teachers with 11 or more years experience at their school compared with students who had teachers with 1 to 5 years of experience at their school (odds ratio [OR] = .511, p = .042). Teacher sex (male), age, possessing a Master's degree or higher, having 11 or more years total teaching experience, and having a teacher with 6 to 10 years of experience at the school did not statistically significantly predict student referral to IC Teams relative to not being referred.

None of the teacher characteristics that predicted student referral to IC Teams relative to not being referred to a problem-solving team statistically significantly predicted referral to CS Teams. Rather, with respect to referral to CS Teams relative to not being referred to a problem-solving team (see Table 16), the odds of referral were 46% lower for students who had teachers that were male compared with students who had teachers that were female (OR = 0.543, p = .020). Additionally, the odds of referral were 30% lower for students who had teachers with 11 or more years of total teaching experience compared with students who had 1 to 5 years of total teaching experience, respectively; (OR = 0.701, p = .039). However, a one standard deviation increase in teacher age was associated with a 22% increase in the odds of referral (OR = 1.216, p = .019). Possessing a Master's degree or higher, or having 6 to 10 or 11 or more years of experience at the school did not statistically significantly predict student referral to CS Teams relative to not being referred.

Question 3: Cross-level interactions. Results from the fully conditional model indicate that for both IC Teams and CS Teams, none of the relationships between student-level characteristics and referral (i.e., level-1 slopes) statistically significantly

varied across teachers using the liberal significance level of $p \leq .10$ for evaluating

homogeneity of level-1 and level-2 slopes. Therefore, there were no cross-level

interactions for which to model moderating effects of teacher characteristics on the

relationship between student-level characteristics and referral. Although this study did

not include any school-level predictors, it should be noted that three of the measures

included in the analysis statistically significantly varied across schools at $p \leq .10$.

Specifically, the relationship between first quarter grades in writing and student referral

statistically significantly varied across schools for IC Teams ($p < .001$), but not for CS

Teams ($p = .338$) relative to not being referred to a problem-solving team. The

relationship between prior behavior ratings for concentration and student referral

statistically significantly varied across schools for both IC Teams ($p = .086$) and CS

Teams ($p = .015$) relative to not being referred to a problem-solving team. Finally, the

relationship between teachers with 11 or more years experience at their school and

student referral statistically significantly varied across schools for IC Teams ($p = .074$),

but not for CS Teams ($p = .352$) relative to not being referred to a problem-solving team.

Multivariate Hypothesis Tests

Results from the multivariate hypothesis tests are summarized in Table 17 and

indicate that several predictors of student referral retained in the fully conditional model

statistically significantly differed between IC Teams and CS Teams at $p \leq .05$. Regarding

the teacher-level predictors, only teacher age statistically significantly differentiated

referrals between the two teams. Specifically, a one standard deviation increase in

teacher age corresponded with a 24% reduction in the odds of student referral to IC

Teams relative to CS Teams (odds ratio [OR] = 0.760, $p = .018$). Being a male teacher,

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possessing a master's degree or higher, having 11 or more years of total teaching experience, and having 6 to 10 or 11 or more years teaching at the school did not statistically significantly differentiate referrals between IC Teams and CS Teams.

Table 17

Differences in Predictors of Referral Between Instructional Consultation Teams and Child Study Teams

Measure	Coefficient Difference	χ^2	Odds Ratio	p-value
Teacher				
Sex (male)	.599	5.558	1.820	.060
Age	-.275	7.942	.760	.018
Master's or Higher	-.245	1.780	.783	>.500
Teaching 11 years +	.333	4.385	1.395	.109
At school 6 to 10 years	-.232	3.316	.793	.188
At school 11 years +	-.636	5.035	.529	.079
Student				
Sex (male)	-.081	10.775	.922	.005
African American	.607	10.838	1.835	.005
Hispanic	-.209	16.616	.811	<.001
Asian/Pacific Islander	-.549	7.852	.577	.019
Unspecified/Other	.846	5.959	2.330	.049
New to District	-.258	7.305	.773	.025
ESOL	.634	5.838	1.885	.052
Special Education	-.308	6.610	.735	.036
Reading	-.207	53.485	.813	<.001
Writing	-.003	36.234	.997	<.001
Math	-.093	62.090	.911	<.001
Concentration	-.153	27.335	.858	<.001
Internalzing	-.143	16.968	.867	<.001
Closeness	.097	24.136	1.102	<.001
Conflict	.115	14.444	1.122	.001

Note. Coefficient Difference = Coefficient$_{(Category\ 1)}$ - Coefficient$_{(Category\ 2)}$. Category 1 = Instructional Consultation Teams. Category 2 = Child Study Teams. ESOL = English as a second or other language.

Regarding the student-level predictors, all but one of the measures retained in the fully conditional model statistically significantly differentiated referrals between IC Teams and CS Teams. Specifically, the odds of referral for male students was 8% lower for IC Teams relative to CS Teams (OR = 0.992, p = .005). For African American and Unspecified/Other race/ethnicity, the odds were 84% and 133% higher for IC Teams relative to CS Teams, respectively (OR = 1.835, p = .005; OR = 2.330, p = .049), while

the odds of referral for Hispanic and Asian/Pacific Islander race/ethnicity were 19% and

42% lower for IC Teams relative to CS Teams, respectively (OR = 0 .811, $p < .001$; OR

= 0.577, p =.019). The odds of referral for students who were new to the district or

eligible for special education the previous year were 23% and 27% lower for IC Teams

relative to CS Teams, respectively (OR = 0.773, p =.025; OR = 0.735, p = .036).

Regarding measures of academic achievement, one standard deviation increases in

quarterly grades for reading, writing, and math corresponded with 19%, 0.3%, and 9%

reductions in the odds of student referral to IC Teams relative to CS Teams, respectively

(OR = 0.813, p <.001; OR = 0.997, $p < .001$; OR = 0.911, $p < .001$). Finally, one

standard deviation increases in prior behavior ratings for concentration and internalizing

problems corresponded with 14% and 13% reductions in the odds of referral to IC Teams

relative to CS Teams, respectively (OR = 0.858, $p < .001$; OR = 0.867, $p < .001$), and for

relationship quality with the prior teacher, one standard deviation increases in closeness

and conflict corresponded with 10% and 12% increases in the odds of referral to IC

Teams relative to CS Teams (OR = 1.102, $p < .001$; OR = 1.122, p = .001). Being a

student for whom English is a second language did not statistically significantly

differentiate referrals between IC Teams and CS Teams.

Chapter 5: Discussion

Introduction

The primary purpose of this study was to identify predictors of elementary school student referrals to problem-solving teams using a broad range of student and teacher characteristics, including the two main reasons teachers report as their basis for referral: student achievement and behavior (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991). Furthermore, this study was conducted in a district that was concurrently implementing two problem-solving team models, IC Teams (Rosenfield & Gravois, 1996) and CS Teams (Moore et al., 1989), which differed in focus, forum and process of problem-solving, and teacher involvement. Therefore, the secondary purpose of this study was to identify and compare student and teacher characteristics that predicted student referrals to IC Teams and CS Teams.

In this chapter, major findings and the implications of this study are discussed. The first section summarizes and interprets the results. Within this section, the findings pertaining to characteristics of students as they relate to referral will be discussed first, followed by the discussion of teacher characteristics, cross-level interactions between student and teacher characteristics, and characteristics of students and teachers that differentiate referral to IC Teams and CS Teams. The second section discusses the implications of the results for research and practice. The third and final section discusses virtues and limitations of the study.

Summary and Interpretation of Results

Student-level predictors. Student characteristics that demonstrated a statistically significant, independent relationship with student referrals to one or both problem-

solving teams relative to not being referred included the following: sex; race/ethnicity; being new to the district; receiving special education services the previous year; reading, writing, and math achievement; prior classroom concentration; prior internalizing behavior; having a close relationship with the prior teacher; and having a conflict laden relationship with the prior teacher. The relevance of these characteristics as predictors varied across problem-solving teams, and with odds ratios ≤ 1.5, the sizes of the effects were small (Chen et al., 2010; Chinn, 2000) suggesting that each individual characteristic likely had a minimal effect on referral. However, the cumulative effect of several characteristics may have a more meaningful effect on referral. Student characteristics that did not statistically significantly predict referral to either of the two problem-solving teams included age (i.e., old for grade, young for grade), FARM, ESOL, and prior externalizing behavior problems.

Statistically significant student characteristics that IC Teams and CS Teams shared in common included sex, Hispanic race/ethnicity, all three measures of academic achievement, prior classroom concentration, and having a close relationship with the prior teacher. Specifically, being male and increases in student-teacher closeness with the prior teacher were associated with increases in the odds of referral, while Hispanic race/ethnicity, increases in achievement, and increases in prior classroom concentration were associated with decreases in the odds of referral. Given that these characteristics predicted student referrals to two teams that differ in theoretical framework, focus, and process, it is possible that these characteristics apply more generally across other problem-solving team models. Furthermore, results pertaining to the role of all three measures of academic achievement and classroom concentration are consistent with

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teacher reports that student academic achievement and behavior are important factors for making student referrals (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991). Results pertaining to the role of sex and race/ethnicity are consistent with concerns raised in the disproportionality literature about intentional or unintentional bias in referral and decision-making processes (CCBD, 2013; Mamlin & Harris, 1998).

Considering that several of the student characteristics statistically significantly predicted referral to IC Teams, but not CS Teams, and vice versa, it seems that there are less general, more model-specific predictors of student referrals to problem-solving teams. Characteristics unique to IC Teams included Asian race/ethnicity, being new to the district, receiving special education services the prior school year, and having a conflict laden relationship with the prior teacher. Specifically, increases in conflict with the prior teacher were associated with increases in the odds of referral, while Asian race/ethnicity, being new to the district, and receiving special education services were associated with decreases in the odds of referral. Characteristics unique to CS Teams included African American and Unspecified/Other race/ethnicity and prior internalizing behavior such that African American and Unspecified/Other race/ethnicity were associated with decreases in the odds of referral, while increases in prior internalizing behavior were associated with increases in the odds of referral. However, it was evident that student race/ethnicity was salient and associated with lower odds of referral to both teams. Contrasts between the student characteristics that predicted referral to IC Teams and CS Teams are summarized and interpreted in a subsequent section.

Finally, findings in the current study regarding the effect of student characteristics on student referrals to problem-solving teams share some similarities and differences

with findings in Pas et al. (2010), the only quantitative research on predictors of referral to problem-solving teams identified through a search of the literature published in peer-reviewed journals within the past 20 years. Both studies identified sex and classroom concentration, but not disruptive or externalizing behavior problems, as predictors of referral. However, the current study did not support findings in Pas et al. of a statistically significant effect for FARM or a non-significant effect for race/ethnicity. Given that Pas et al. did not include measures of academic achievement, and previous research has found a statistically significant relationship between FARM and achievement (Burnett & Farkas, 2008; Kieffer, 2010), the effect of FARM on referral in Pas et al. may have been spurious. Furthermore, the predominantly African American (59%) and Caucasian (29%) student sample population in Pas et al. may have limited the study's ability to detect the effects of student race/ethnicity on student referrals across different racial/ethnic groups.

Teacher-level predictors. The teacher characteristics that demonstrated a statistically significant, independent relationship with student referrals to IC Teams or CS Teams relative to not being referred to a problem-solving team included sex, age, 11+ years of total teaching experience, and 11+ years of experience at the current school. However, with odds ratios ≤ 1.5, the sizes of the effects were small (Chen et al., 2010; Chinn, 2000), and one of the statistically significant teacher characteristics were shared in common across problem-solving teams. In fact, most of the teacher characteristics considered in this study did not statistically significantly predict referral to either of the two problem-solving teams, including non-Caucasian race/ethnicity, holding a master's degree or higher, 6 to 10 years of total teaching experience, 6 to 10 years of experience at the current school, teacher efficacy, collaboration, job satisfaction, and instructional

practices. Considering that teachers were making the referral decisions, the lack of statistical significance for most of the teacher characteristics, particularly those associated with teacher beliefs and practices, was somewhat unexpected.

Given that very few teacher characteristics predicted student referrals, and none of the characteristics were shared in common across IC Teams and CS Teams, it seems possible that teacher characteristics may have a limited, inconsistent role as predictors of student referrals to problem-solving teams. However, across both IC Teams and CS Teams it was evident that some aspect of advanced work experience was salient and associated with decreased odds of student referrals to both teams. It is possible that veteran teachers may have been less inclined to make referrals because they had acquired the knowledge and skill necessary to support their struggling students without assistance. Specifically, only one teacher characteristic predicted student referrals to IC Teams, such that having 11+ years of experience at the current school was associated with lower odds of student referrals. Characteristics that uniquely predicted student referrals to CS Teams included sex, age, and 11+ years total teaching experience such that male teachers and teaching 11+ years were associated with lower odds of student referrals; and increases in teacher age were associated with increases in the odds of student referrals. This finding of an opposite relationship with referral for years teaching and teacher age was unexpected given the statistically significant positive correlation ($r = .61$, $p \leq .05$) found between the two measures when conducting multicolinearity diagnostics. However, it is important to note that although age and experience were positively correlated, they were not perfectly correlated. Furthermore, the measures are different constructs that used different scaling methods and were being considered independently given all other

measures in this study. The specific contrasts between teacher predictors of referral to IC Teams and CS Teams are summarized and interpreted in a subsequent section.

Finally, findings in the current study regarding the effect of teacher characteristics on student referrals to problem-solving teams share some similarities and differences with findings in Pas et al. (2010). Both studies identified sex, but not non-Caucasian race/ethnicity or holding a graduate degree, as a predictor of student referrals. However, as was previously stated, the current study found that teacher sex statistically significantly predicted student referrals for CS Teams only. Furthermore, the current study did not support findings in Pas et al. of a statistically significant effect for teacher efficacy or a non-significant effect for teaching experience. These dissimilar findings within and across the two studies lend further support to the possibility that teacher characteristics may have a limited, inconsistent role as predictors of student referrals to problem-solving teams.

Interactions between student- and teacher-level predictors. Considering the concerns raised in the disproportionality literature about intentional or unintentional bias in referral and decision-making processes (CCBD, 2013; Mamlin & Harris, 1998) and that decisions about student referrals to problem-solving teams are made by teachers, it was thought that teachers may be influenced by student characteristics differently such that the relationship between student characteristics and student referrals would vary across teachers. However, none of the relationships between student characteristics and student referrals to IC Teams or CS Teams relative to not being referred to a problem-solving team statistically significantly varied across teachers. In other words, teachers seemed to be considering and placing equal weight on the same student characteristics

when making referral decisions. Therefore, if intentional or unintentional bias is salient in decisions to refer students to problem-solving teams, it seems that teachers share similar biases irrespective of teachers' personal characteristics included in the present study.

Rather than varying across teachers, findings indicate that the relationship between some of the characteristics considered and student referrals to problem-solving teams varied across schools. Specifically, the relationship between prior classroom concentration and student referrals statistically significantly varied across schools for both IC Teams and CS Teams relative to not being referred to a problem-solving team. Additionally, the relationship between writing achievement and student referrals statistically significantly varied across schools for IC Teams, as did the relationship between teachers with 11+ years of experience at the current schools and student referrals. In other words, the extent to which prior concentration problems influenced the odds of student referrals to both teams differed across schools, as did the extent to which writing achievement and advanced teacher experience in the school influenced the odds of student referrals to IC Teams. These findings suggest that school characteristics may be an important source of variation in student referrals to problem-solving teams.

Differences between predictors of referral to IC Teams and CS Teams.
Among the student characteristics retained in the fully conditional multinomial HGLM, all but one, ESOL, statistically significantly differentiated the odds of student referrals to IC Teams relative to CS Teams. With odds ratios ≤ 2.5, the sizes of the effects were small (Chen et al., 2010; Chinn, 2000) suggesting that, individually, each characteristic likely had a minimal effect on differentiating referral between the two problem-solving teams. However, the cumulative effect of several characteristics may have a more

meaningful effect on differentiating referral. The odds of referral to IC Teams relative to CS Teams were higher for African American and Unspecified/Other race/ethnicity. Additionally, the odds of referral to IC Teams were higher with increases in closeness and conflict with the prior teacher, suggesting that agreeableness in the student-teacher relationship was not a factor in teachers' decisions to choose IC Teams over CS Teams. However, considering that IC Teams required more teacher involvement than CS Teams, this finding suggests that teachers may have been more willing to invest time in problem-solving for struggling students with a history of student-teacher familiarity or frequent student-teacher interactions.

Regarding the odds of referral to CS Teams relative to IC Teams, the odds were higher for males, Hispanic and Asian race/ethnicity, receiving special education services the previous school year, and being new to the district. The higher odds of referral to CS Teams for prior special education eligibility may reflect the historical ties between CS Teams and the special education referral and decision-making process (Moore et al., 1989), and the higher odds of referral to CS Teams for new students further suggests that increased student-teacher familiarity may have influenced teachers' decisions to choose IC Teams. Moreover, the odds of referral to CS Teams were higher with increases in reading, writing, and math achievement, prior classroom concentration, and prior internalizing behavior problems, suggesting that teachers chose IC Teams over CS Teams to address more problematic academic concerns and disruptive classroom behaviors. This finding further suggests that teachers may have perceived IC Teams, with its emphasis on instructional assessment, a systematic problem-solving and intervention

process, and regular follow-up support, as more useful or able to address more serious academic or behavior problems as compared with CS Teams.

Although four teacher characteristics were retained in the fully conditional multinomial HGLM, only one characteristic, age, statistically significantly differentiated the odds of student referrals to IC Teams relative to CS Teams. Specifically, the odds of referral to CS Teams were higher with increases in age, suggesting that the more district-established, child-focused, and limited teacher involvement approach of CS Teams may have appealed more to older teachers, while the more novel, teacher-focused, and high teacher involvement approach of IC Teams may have appealed more to younger teachers. The odds of student referrals did not statistically significantly differ between IC Teams and CS Teams for teachers who were male, possessed a master's degree or higher, had 11 or more years of total teaching experience, or had 6 to 10 or 11 or more years teaching at the school.

Virtues and Limitations

Although research on the characteristics of students and teachers that predict student referrals to problem-solving teams has important implications for the effective and equitable provision of intervention supports within the general education setting, the available literature is scarce such that only one quantitative study (Pas et al., 2010) was found during a search of peer-reviewed journals published within the past 20 years. While the literature on predictors of referral to special education is somewhat more prevalent, students referred to problem-solving teams and special education are somewhat different sample populations, and findings may not be analogous across the two populations of students. Therefore, the primary virtue of the present study resides in

the contribution to the scant body of literature on predictors of student referrals to problem-solving teams.

However, the current study has several additional virtues. First, it includes a large, diverse sample of students and teachers, and uses advanced statistical analysis procedures that address problems due to missing data and the nesting of students within teachers and schools. Second, it addresses a significant limitation found across the available literature on referral to problem-solving teams and special education by considering the effect of both reasons teachers report as their reason for referral: student academic achievement and behavior (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991). Third, it includes several new student and teacher characteristics that have not previously been considered in the literature, but are relevant to the study of student referrals to problem-solving teams due to their relationship with academic achievement and/or behavior. Fourth, it takes a comprehensive approach to identifying characteristics of students and teachers that predict student referrals to problem solving teams by considering the predictors collectively, thereby providing the opportunity to identify their unique contribution to student referrals above and beyond shared variance. Finally, this study is the only one of its kind to consider school problem-solving teams that differ in theoretical framework, focus, and process, and identify similarities and differences in predictors of student referrals to the different problem-solving team models.

Although the current study has many virtues, it is not without limitations, which include generalizability, missing data, model misspecification, and the constraints of the standard statistical analysis software. First, data in this study were collected within the elementary school setting; therefore, the findings may not generalize to a middle school

or high school setting. Furthermore, the data were collected within a single school district that was participating in a large-scale, experimental evaluation of Instructional Consultation Teams (Rosenfield & Gottfredson, 2010), and as such, was concurrently operating two problem-solving team models. When teachers made referral decisions, they were presented with a unique opportunity to choose between problem-solving teams, which may have affected their decisions in ways that might not have occurred had only one problem-solving team been available. Therefore, it is conceivable that the results may not generalize across other schools or districts, particularly those in which teachers do not have a choice of problem-solving team.

Second, almost every measure included in this study had missing data; however, the overall amount of missing information, or the number of missing values in the data matrix, was relatively small. The missing data were imputed using multiple imputation, which yields relatively unbiased parameter estimates when results are pooled across imputations (Allison, 2000; Enders, 2010a; Shafer & Graham, 2002).   Furthermore, the imputation model included auxiliary variables as predictors to increase statistical power, reduce non-response bias, and strengthen the assumptions that data were missing at random, and it attempted to preserve higher order relationships so that the magnitude of the effects were not attenuated when evaluating predictors of student referrals to problem-solving teams. Nonetheless, data imputation is less reliable for measures with a high proportion of missing values, and the imputation model may not have been sufficiently specified, thereby introducing bias. As such, missing data remains a plausible limitation.

Third, the model used to predict student referrals to problem-solving teams may have been misspecified in a manner that contributed to omitted-variable bias (Begg & Lagakos, 1990). Omitted-variable bias occurs when predictors that are correlated with both the outcome and one or more other predictors in the model are excluded from the model. It is possible that characteristics of students and teachers associated with student referrals to problem-solving teams were not measured, and as such, were not included in the model. Furthermore, this study partitions and controls for variance associated with classroom and school contexts; however, the effect of environmental context, or the effect of characteristics aggregated to the cluster level, on student referrals to problem-solving teams above and beyond the unique effect of individual level measures was not evaluated. Therefore, the effects of student and teacher characteristics in the current study may have been over- or underestimated.

Fourth, commonly used statistical analysis software was chosen over more specialized software packages, such as MLwiN with REALCOM-IMPUTE (Carpenter, Goldstein, & Kenward, 2011) or packages within the R language environment (R Development Core Team, 2011), that are available for imputing multilevel data or analyzing a large number of multiply imputed data sets. Specifically, IBM SPSS Statistics 22.0 for Windows was selected for multiply imputing the data; however, the software package does not include an algorithm for imputing multilevel data, and data were imputed using flat files. Although using a flat file to impute multilevel data may be inconsequential when the fraction of missing data is small (Zhang, 2005), and data were imputed in a manner that made use of the nested data structure, the failure to account for nesting may have underestimated standard errors and produced biased parameter

estimates in the multiply imputed data set (Luke, 2004; Raudenbush & Bryk, 2002). Furthermore, HLM 7.01 (Raudenbush et al., 2001) was used to analyze the multiply imputed data sets; however, HLM 7.01 is limited to handing $m = 10$ imputed data sets. Although this number of imputations is sufficient for maximizing relative efficiency when the fraction of missing information, or unexplained variation in the data matrix, is small (Enders 2010a), as is the case in the current study, as many as $m = 20$ imputed data sets would have been ideal for maximizing statistical power (Graham et al., 2007).

While not necessarily a set of limitations, there were two specific challenges this study faced that are commonly encountered when conducting applied, school-based research. The first challenge concerned the use of student grades as measures of academic achievement and teacher completed rating scales as measures of student behavior. Rather than being objective measures of student performance, both measures rely heavily on teacher input and are therefore influenced, at least in part, by teacher preferences and tolerances. Although student performance on standards-based measures of reading, writing, and math, as well as direct observations of student behavior might have provided more objective measures, there were barriers to their use. Specifically, as is the case with many school districts, standards-based measures of achievement were administered annually, but they were not administered at each grade level. Additionally, the substantial resources that would have been required for researchers to directly observe and collect data on an entire district of students rendered that method of measuring student behavior impractical.

The second challenge concerned the use of prior teacher ratings of student behavior and student-teacher relationship quality. Researchers in the original study from

which this data were collected (Rosenfield & Gottfredson, 2010) administered teacher surveys during the middle of the school year, thereby allowing teachers ample time to observe and get to know their students before rating behavior. Because these ratings may have been influenced by student referral decisions and intervention efforts that already had taken place, prior teacher ratings were chosen to ensure temporal precedence of the predictors. Using prior teacher ratings provided the opportunity to consider the influence of prior student behavior and student-teacher relationship quality on student referrals to problem-solving teams. However, ratings from prior and referring teachers may differ; therefore, the results from the current study are unable to account for the influence of referring teachers' perceptions of student behavior and student-teacher relationship quality on their referral decisions.

Implications for Practice and Research

The ultimate objective of this study was to yield information useful for ensuring the equitable provision of intervention supports to struggling students within the general education setting. According to Slonski-Fowler and Truscott (2004), problem-solving teams are the most common vehicle through which struggling students within the general education setting receive intervention supports. Findings from the current study support teachers' assertions that student academic achievement and behavior are important factors for making student referrals to problem-solving teams (Briesch et al., 2010; Del'Homme et al., 1996; Lloyd et al., 1991); however, the findings also support concerns raised in the disproportionality literature that individual factors other than academic achievement or behavior are salient and result in intentional or unintentional bias when making student referrals (CCBD, 2013; Mamlin & Harris, 1998). Specifically,

controlling for all other characteristics considered in this study, including academic achievement and behavior, female and racially/ethnically diverse students had lower odds of referral to both problem-solving teams, and therefore, to intervention supports as well. Furthermore, findings indicate that students whose teachers have 11+ years of total teaching experience or teaching at the school had lower odds of referral to both problem-solving teams. Given that teachers refer students to problem-solving teams, it is evident that teacher outreach and training is needed in order to help teachers recognize and learn strategies for addressing these disparities in student access to problem-solving teams and intervention supports. Additionally, the findings suggest that alternative procedures through which students gain access to intervention supports, such as through the implementation of universal screening methods (Dowdy et al., 2015), are worth exploring for their ability to support the equal access of all students to interventions.

As a final point, the methods and findings in the current study present several avenues for future research. First, the body of literature on predictors of student referrals to problem-solving teams is scant, and additional research is needed overall, as well as across different sample populations and problem-solving team models in order to clarify the characteristics of students and teachers that apply generally across problem-solving team models and those characteristics that may be model specific. Second, the finding that intentional or unintentional bias was evident when teachers referred students to problem-solving teams suggests that additional research is needed to determine if student access to interventions is more equitable through alternative methods, such as universal screening procedures whereby all students below an identified benchmark level of performance are identified for intervention.

Third, the findings in this study suggest that school characteristics may be an important source of variation in student referrals to problem-solving teams. For example, the odds of student referral may have been influenced by the prevalence of problem-solving team use in a school as well as the availability of alternative resources to support struggling students, which may vary according to school size and socioeconomic status of the overall student population. However, the current study did not include any school-level characteristics as predictors. Therefore, additional research is needed that considers the possible effect of school characteristics on student referrals to problem-solving teams above and beyond student and teacher characteristics.

Fourth, the current study did not consider the effect of individual level aggregates at different levels of clustering above and beyond the unique effect of individual level measures. When individual level measures are aggregated to higher levels of clustering, they generate measures of the environmental context or climate that are unique in construct from the individual measure. Regarding predictors of student referrals to problem-solving teams, it seems possible that aspects of the classroom or school climate, such as classroom- or school-level student achievement, classroom- or school-level student behavior, or school-level teacher collaboration, might be salient above and beyond individual student or teacher characteristics. For example, students may stand out more to teachers and be selected for referral when their academic achievement or behavior differs significantly from classroom or school averages. Furthermore, teachers in highly collaborative schools may be more willing to make student referrals and problem-solve with their peers than teachers in schools that are less collaborative.

Therefore, additional research is needed that considers the effect of the classroom and school climate on student referrals to problem-solving teams.

Finally, the virtues and limitations of this exploratory quantitative study suggest that future research on student referrals to problem-solving teams may benefit from the use of multi-method approaches, such as a combination of quantitative and qualitative research methods. For example, including qualitative methods, such as interviews with a random subset of referring and non-referring teachers, may provide additional opportunities to understand the processes by which teachers make referral decisions. Teachers' reasons for choosing not to refer students to problem-solving teams, expectations for student outcomes following problem-solving team referral, and awareness of referral biases are among the many relevant topics or questions that could be answered through teacher interviews.

Appendix A

Literature on Student Demographic Characteristics and Student Achievement or Behavior

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Crothers et al. (2010)	276 students	Chi-Square	*Student* demographics, teacher ratings of behavior.	Positive effect of being old for grade on relational, verbal, and physical bullying behavior. Positive effect of being old for grade on passive and provocative victim behavior.
Downey & Pribesh (2004)	12,989 students	Multilevel Modeling	*Student* demographics, teacher ratings of behavior. *Teacher* demographics, experience. *School* demographics, sector.	Positive effect of African-American race on problem behaviors. Negative effect of African-American race on effective habits of work.
Henninger & Luze (2012)	1,067 students	Latent Growth Modeling (SEM)	*Student* demographics, parent ratings of behavior.	No effect of sex on externalizing. Significant interaction of sex and SES on externalizing with increased time in poverty associated with increased externalizing behaviors for girls, but not boys.
Hsin & Xie (2014)	1,612 students	Multilevel Growth Modeling	*Student* demographics, criterion-referenced measures of reading and math, teacher ratings of proficiency in reading, math, and general knowledge, teacher ratings of academic effort.	Positive effect of Asian race on gains in academic effort and teacher ratings of academic proficiency. No significant effect of Asian race on gains in measures of reading and math.
Huang & Invernizzi (2012)	405 students	Multilevel Growth Modeling	*Student* demographics, criterion-referenced measures of early literacy skills.	Negative effect of young for grade on early literacy skills. Positive effect of young for grade on gains in early literacy skills.

Literature on Student Demographic Characteristics and Student Achievement or Behavior (continued)

Study	Sample Size (N)	Data Analysis	Measures	Relevant Findings
Lachance & Mazzocco (2006)	249 students	ANOVA, T-test, and SEM	*Student* demographics, norm-referenced measures of math, reading, and visual-spatial skills.	Positive effect of female sex on letter-word identification across years and on reading fluency in 3rd grade. Positive effect of female sex on geometry and math fact accuracy. Positive effect of male sex on numeration and time/money. No significant effect of sex on math calculation or counting. No significant effect of sex on growth rates for math, reading, or visual-spatial skills.
McIntosh, Reinke, Kelm, & Sadler (2013)	473 students	ANOVA	*Student* demographics, norm-referenced measures of oral reading fluency, office discipline referrals.	No significant effect of sex on reading skill. Significant interaction effect of sex and grade level on discipline referrals with increases in referrals over time for boys but not girls.
Miner & Clarke-Stewart (2008)	1,171 students	Multilevel Growth Modeling	*Student* demographics, teacher ratings of behavior, caregiver ratings of temperament, behavior, and discipline procedures.	Positive effect of male sex and African-American race on teacher ratings of externalizing behavior. Effect of race on teacher ratings of externalizing behavior increased over time.
NICHD Early Child Care Research Network (2007)	913 students	Multilevel Growth Modeling	*Student* demographics, norm-referenced measures of reading and math, teacher ratings of literacy, mathematical thinking, behavior, and student-teacher relationship.	Negative effect of kindergarten entry age on letter-word identification. Positive effect kindergarten entry age on teacher ratings of literacy and mathematical thinking, and gains on norm-referenced measures of reading and math. No significant effect of kindergarten entry age on teacher ratings of behavior or student-teacher relationship.

Literature on Student Demographic Characteristics and Student Achievement or Behavior (continued)

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Peters, Kranzler, Algina, Smith, & Daunic (2014)	982 students 65 teachers 11 schools	Multilevel Modeling	*Student* demographics, teacher ratings of behavior. *Teacher* demographics, efficacy. *School* demographics.	Negative effect of male sex and Hispanic race on internalizing behavior. Negative effect of male sex and positive effect of African-American race on externalizing behavior. Positive effect of male sex and negative effect of African-American race on social skills. Positive effect of male sex and negative effect of African-American race on ratings of competence.
Plata & Masten (1998)	234 students 12 teachers	Chi-Square	*Student* demographics, teacher nominations for GT program, teacher ratings of learning, motivation, creativity, and leadership.	Negative effect of Hispanic race on GT program nominations. Negative effect of Hispanic race on ratings of learning, motivation, creativity, and leadership.
Scheiber, Reynolds, Hajovsky, & Kaufman (2015)	1,574 students	Path Analysis (SEM)	*Student* demographics, norm-referenced measure of reading, writing, and math.	Positive effect of female sex on reading and writing. No effect of sex on math.
Stipek & Byler (2001)	237 students	ANOVA	*Student* demographics, self-report measures of school liking and academic skills, norm-referenced measures of reading and math, criterion-reference measures of reading and writing, teacher ratings of academic performance, social competence, academic engagement, and student-teacher relationship.	Positive effect of kindergarten entry age on norm-referenced measures of reading and math, and self-reported school liking at end of kindergarten. Effect on reading and math no longer significant at end of 3rd grade.

Note. ANOVA = Analysis of variance. GT = Gifted and talented. SEM = Structural equation modeling. SES = Socioeconomic status.

Appendix B

Literature on Student Services Received and Student Achievement or Behavior

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Burnett & Farkas (2008)	8,331 students	Multilevel Growth Modeling	*Student* demographics, family structure, region, urbanicity, norm-referenced measures of math. *Mother* demographics, norm-referenced measure of cognitive ability.	Negative effect of poverty on math for children 10 years of age or younger. No significant effect of poverty on math among children 10-15 years of age.
Christ, Silberglitt, Yeo, & Cormier (2010)	3,808 students	Multilevel Growth Modeling	*Student* grade level, services, curriculum-based measures of oral reading fluency.	Negative effect of special education on gains in oral reading fluency over a 1-year period.
Dawson & Williams (2008)	2,840 students	Multilevel Growth Modeling	*Student* demographics, teacher ratings of behavior, criterion referenced measures of English language proficiency	No significant effect of limited English proficiency on Hispanic students' internalizing behaviors in grades K-3 or externalizing behaviors in grades K-2. Positive effect of limited English proficiency on Hispanic students' externalizing behaviors in 4th grade.
Dearing, McCartney, & Taylor (2006)	1,132 students	Multilevel Growth Modeling	*Student* demographics, family structure, parent and teacher ratings of behavior.	Positive effect of chronic poverty on externalizing and internalizing. No significant effect of transient poverty on externalizing or internalizing. Negative effect of family income on externalizing. Significant interaction of poverty and income on externalizing with chronic poverty showing larger decreases in externalizing as income increased than transient or never poor.

Literature on Student Services Received and Student Achievement or Behavior (continued)

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Han (2010)	14,853 students	Multilevel Growth Modeling	*Student* demographics, criterion-referenced measures of English language proficiency, teacher ratings of behavior. *School* demographics, services, learning environment, facilities, sector.	Negative effect of fluent or Spanish-dominant bilingualism on kindergarten externalizing behavior, and limited English proficiency on kindergarten interpersonal skills. Positive effect of fluent or Spanish-dominant bilingualism and Spanish monolingualism on gains in effective habits of work and interpersonal skills.
Henninger & Luze (2012)	1,067 students	Latent Growth Modeling (SEM)	*Student* demographics, parent ratings of behavior.	Significant interaction of sex and SES on externalizing with increased time in poverty associated with increased externalizing behaviors for girls, but not boys.
Kieffer (2008)	17,385 students	Multilevel Growth Modeling	*Student* demographics, criterion referenced measures of reading and English language proficiency. *School* demographics.	Positive effect of entering kindergarten with language minority status and oral English language proficiency on reading in 5th grade. Negative effect of entering kindergarten with language minority status and limited oral English language proficiency on reading in 5th grade; positive effect on reading gains from kindergarten through 5th grade.
Kieffer (2011)	9,189 students	Latent Growth Modeling (SEM)	*Student* demographics, criterion referenced measures of reading and English language proficiency. *School* demographics.	Negative effect of language minority status on fall kindergarten reading. Positive effect of entering kindergarten with language minority status on gains in reading. Period of strongest gains correspond with period after oral English language proficiency was acquired.

Literature on Student Services Received and Student Achievement or Behavior (continued)

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Kieffer (2012)	9,189 students	Latent Growth Modeling (SEM)	*Student* demographics, criterion referenced measures of reading. *School* demographics.	Positive effect of SES on reading in kindergarten. Negative effect of SES on gains in reading from K-3rd grade. Positive effect of SES on gains in reading from 3rd-8th grade.
Kieffer & Vukovic (2013)	166 students	Latent Growth Modeling (SEM)	*Student* demographics, norm-referenced measures of reading and working memory.	Negative effect of language minority status on vocabulary and oral comprehension. No significant effect of language minority status on gains in reading or working memory.
Peters, Kranzler, Algina, Smith, & Daunic (2014)	982 students 65 teachers 11 schools	Multilevel Modeling	*Student* demographics, teacher ratings of behavior. *Teacher* demographics, efficacy. *School* demographics.	No statistically significant effect of FARM on ratings of internalizing, externalizing, or social skills. Negative effect of FARM on ratings of competence.
Schulte & Stevens (2015)	92,045 students	Multilevel Growth Modeling	*Student* demographics, services, criterion-referenced measures of math.	Negative effect of special education on gains in math over a 4-year period. Effects observed for students currently eligible as well as for students previously exited from special education.

Note. FARM = Free and reduced meals. SEM = Structural equation modeling. SES = Socioeconomic status.

Appendix C

Literature on Student-Teacher Relationship Quality and Student Achievement or Behavior

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Baker (2006)	1,310 students 68 teachers	Generalized Linear Modeling	*Student* norm-referenced measures and grades in reading, teacher ratings of student-teacher relationship, behavior, classroom adjustment, and social skills.	Positive relationship between student-teacher relationship quality and reading grades, classroom adjustment, social skills. Student sex, externalizing problems, and internalizing problems moderate the relationship between student-teacher relationship quality and reading, classroom adjustment, and social skills.
Baker, Grant, & Morlock (2008)	423 students 68 teachers	Multivariate Generalized Linear Modeling	*Student* grades in reading and work habits, teacher ratings of student-teacher relationship, behavior, and classroom adjustment.	Positive relationship between closeness and reading, classroom adjustment. Negative relationship between conflict and reading, work habits, classroom adjustment. Closeness moderates the relationship between externalizing behavior and reading. Conflict moderates the relationship between internalizing and both work habits and classroom adjustment.
Birch & Ladd (1997)	206 students 16 teachers	Multiple Regression	*Student* demographics, norm-referenced measures of academic readiness, self-report measures of social adjustment and attitudes toward school, teacher ratings of student-teacher relationship and school adjustment.	Positive relationship between closeness and academic readiness, school liking. Negative relationship between conflict and school liking, cooperative participation.

Literature on Student-Teacher Relationship Quality and Student Achievement or Behavior (continued)

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Fowler, Banks, Anhalt, Der, & Kalis (2008)	230 students 20 teachers	ANOVA & Multiple Regression	*Student* services received, teacher ratings of student-teacher relationship, mathematical thinking, literacy development, behavior. *Teacher* demographics.	Positive relationship between conflict and externalizing; closeness and prosocial behavior; overall relationship quality with ratings of academic performance. Negative relationship between closeness and externalizing; conflict and prosocial behavior.
McCormic & O'Connor (2015)	1,118 students	Multilevel Growth Modeling	*Student* demographics, norm-referenced measures of math and reading, teacher ratings of student-teacher relationship	Negative effect of conflict on reading. Positive relationship between improvements in closeness and gains in reading. Significant interaction of sex and conflict on math with lower achievement for girls with conflict than boys with conflict.

Note. ANOVA = Analysis of variance.

Appendix D

Literature on Teacher Demographic Characteristics and Student Achievement or Behavior

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Croninger, Rice, Rathbun, & Nishio (2007)	5,167 students 1,342 teachers 453 schools	Multilevel Modeling	*Student* demographics, criterion referenced measures of reading and math. *Teacher* demographics, qualifications, experience. *School* aggregated teacher and student measures.	No significant effect of teacher age on gains in reading or math.
Downey & Pribesh (2004)	12,989 students	Multilevel Modeling	*Student* demographics, teacher ratings of behavior. *Teacher* demographics, experience. *School* demographics, sector.	Significant interaction of teacher race and student race on ratings of behavior with Caucasian teachers rating African-American students having more externalizing problems than Caucasian students.
Fowler, Banks, Anhalt, Der, & Kalis (2008)	230 students 20 teachers	ANOVA	*Student* services received, teacher ratings of student-teacher relationship, mathematical thinking, literacy development, behavior. *Teacher* demographics.	Positive effect of African American teacher race on ratings of student prosocial behavior. No significant effect of teacher race on ratings of student externalizing behavior, academic performance, or student-teacher relationship quality.
Peters, Kranzler, Algina, Smith, & Daunic (2014)	982 students 65 teachers 11 schools	Multilevel Modeling	*Student* demographics, teacher ratings of behavior. *Teacher* demographics, efficacy. *School* demographics.	Teacher age mediates the relationship between student sex and externalizing problems with increases in age associated with decreased differences in externalizing between boys and girls.
Pigott & Cowan (2000)	445 students 70 teachers 24 schools	MANOVA	*Student* demographics, teacher ratings of behavior and future academic expectations. *Teacher* demographics, use of negative descriptors.	Positive effect of African American teacher race on ratings of student competencies and expectations. Negative effect of African American teacher race on ratings of student problem behaviors.

Literature on Teacher Demographic Characteristics and Student Achievement or Behavior (continued)

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Taylor, Gunter, & Slate (2001)	186 teachers	ANOVA	*Student* demographics, teacher ratings of behavior. *Teacher* demographics.	Significant interaction of teacher sex, student sex, and student race with male teachers rating more problem behaviors for African-American female students.

Note. ANOVA = Analysis of variance. MANOVA = Multivariate analysis of variance.

Appendix E

Literature on Teacher Experience and Student Achievement or Behavior

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Clotfelter, Ladd, & Vigdor (2007)	1 million student observations over 10-years	Longitudinal, Value-Added Modeling	*Student* demographics, standards-based measures of reading and math. *Teacher* demographics, qualifications, experience.	No significant effect of teacher education level on gains in reading and math. Positive effect of years teaching on gains in reading and math.
Croninger, Rice, Rathbun, & Nishio (2007)	5,167 students 1,342 teachers 453 schools	Multilevel Modeling	*Student* demographics, criterion referenced measures of reading and math. *Teacher* demographics, qualifications, experience. *School* aggregated teacher and student measures.	No significant effect of teacher education level on gains in reading or math. Positive effect of holding a degree in elementary education on gains in reading. Small, negative effect of the school's teacher education level on gains in math. No significant effect of years teaching on gains in reading or math.
Guarino, Hamilton, Lockwood, Rathbun, & Hausken (2006)	16,308 students 3,305 teachers	Multilevel Modeling	*Student* demographics, criterion referenced measures of reading and math. *Teacher* experience, instructional practices. *School* demographics, sector, region, urbanicity.	No significant effect of teacher education level on gains in reading and math. No significant effect of years teaching the measured grade level on gains in reading and math.
Huang & Moon (2009)	1,544 students 154 teachers 53 schools	Multilevel Modeling	*Student* demographics, norm-referenced measures of reading. *Teacher* qualifications, experience, class composition. *School* SES.	No significant effect of teacher education level on reading. Positive effect for years teaching (5+ years) on reading. Positive effect for years teaching the measured grade level on reading.

Note. SES = Socioeconomic status.

Appendix F

Literature on Teacher Beliefs or Practices and Student Achievement or Behavior

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Firminder, Gavin, & McCoach (2014)	560 students 34 teachers	Multilevel Modeling	*Student* grade level, norm-referenced and researcher-developed measures of math. *Teacher* instructional practices.	Positive effect of teacher use of verbal communication and math language on gains in math.
Goddard, Goddard, & Tschannen-Moran (2007)	2,536 students 452 teachers 47 schools	Multilevel Modeling	*Student* demographics, norm-referenced measures of reading and math, standards-based measures of reading and math. *Teacher* collaboration. *School* demographics.	Positive effect of aggregated school-level teacher collaboration on reading and math.
Goddard, Hoy, & Woolfolk Hoy (2000)	47 schools	Multilevel Modeling	*Student* demographics, norm-referenced measures of student reading and math. *Teacher* collective efficacy.	Positive effect of collective teacher efficacy on reading and math.
Goddard, Miller, Larson, & Goddard (2010)	1600 teachers 96 schools	Path Analysis (SEM)	*Student* standards-based measures of reading and math. *Teacher* instructional leadership, collaboration. *School* demographics.	Positive direct effect of aggregated school-level teacher collaboration on mean school reading and math.
Guarino, Hamilton, Lockwood, Rathbun, & Hausken (2006)	16,308 students 3,305 teachers	Multilevel Modeling	*Student* demographics, criterion referenced measures of reading and math. *Teacher* experience, instructional practices. *School* demographics, sector, region, urbanicity.	Positive effect of teacher instructional practices on gains in reading and math.
Hines & Kritsonis (2010)	302 students	ANOVA	*Student* demographics, standards-based measures of math. *Teacher* efficacy.	Positive effect of teacher efficacy on math.
Johnson, Kraft, & Papay (2012)	25,135 teachers 1,142 schools	Multiple Regression	*Teacher* demographics, experience, job satisfaction. School demographics, urbanicity, sector, standards-based measures of math and reading.	Positive effect of teacher job satisfaction with working conditions on gains in reading and math.

Literature on Teacher Beliefs or Practices and Student Achievement or Behavior (continued)

Study	Sample Size (*N*)	Data Analysis	Measures	Relevant Findings
Klassen & Chiu (2010)	1,430 teachers	Path Analysis (SEM)	*Teacher* demographics, experience, efficacy, stress, job satisfaction.	Positive relationship between job satisfaction and teacher efficacy for classroom management and instructional practices.
McCarthy, Lambert, & Reiser (2014)	185 teachers	ANOVA	*Teacher* experience, job satisfaction, stress, coping strategies, commitment	Positive relationship between job satisfaction and career commitment. Positive relationship between job satisfaction and strategies for coping with job stress.
McCoach & Colbert (2010)	44 schools	Multilevel Path Analysis (SEM)	*School* demographics, percent of students reaching mastery on standards-based measures of reading, writing, and math. *Teacher* collective efficacy.	Collective teacher efficacy mediates the relationship between school SES and academic achievement. Positive direct relationship between collective efficacy and achievement.
Palardy & Rumberger (2008)	3,496 students 877 teachers 253 schools	Multilevel Modeling	*Student* demographics, criterion referenced measures of reading and math. *Teacher* experience, attitudes, instructional practices.	Positive effect of teacher instructional practices on gains in reading and math.
Peters, Kranzler, Algina, Smith, & Daunic (2014)	982 students 65 teachers 11 schools	Multilevel Modeling	*Student* demographics, teacher ratings of behavior. *Teacher* demographics, efficacy. *School* demographics.	Teacher efficacy for classroom management mediates the relationship between student race and externalizing problems, student race and social skills.
Schacter, Thum, & Zifkin	816 students 48 teachers	Path Analysis (SEM)	*Student* norm-referenced measures of reading, math, and language. *Teacher* instructional practices, classroom climate.	Positive relationship between teacher instructional practices that elicit student creativity and gains in reading, math, and language.

Literature on Teacher Beliefs or Practices and Student Achievement or Behavior (continued)

Study	Sample Size (N)	Data Analysis	Measures	Relevant Findings
Tschannen-Moran & Barr (2004)	66 schools	Multiple Regression	*Student* standards-based measures of math, reading, and writing. *Teacher* collective efficacy. *School* demographics.	Positive correlation between collective teacher efficacy and mean school math, reading, and writing. Positive effect of collective teacher efficacy on mean school writing.
Wolters & Daugherty (2007)	1,024 teachers	Multiple Regression	*Teacher* grade taught, experience, efficacy, instructional practices.	Positive effect of teacher efficacy on use of instructional practices that foster mastery goals.
Xue & Meisels (2004)	13,609 students 2,690 teachers 788 schools	Multilevel Modeling	*Student* demographics, criterion-referenced measures and teacher ratings of literacy. *Teacher* experience, instructional practices for literacy. *School* demographics, sector, region, urbanicity.	Positive effect of teacher instructional practices on gains in reading.

Note. ANOVA = Analysis of variance. SEM = Structural equation modeling.

Appendix G

Quantitative Research on Predictors of Referral to School Problem-Solving Teams

Study	Sample Size (*N*)	Data Source	Data Analysis	Level of Independent Measures	Results		Strengths and Limitations
					Significant	Not Significant	
Pas, Bradshaw, Hershfeldt, & Leaf (2010)	9795 students, 491 teachers, 31 schools	School Records	Multilevel Logistic Regression	Student Teacher School	*Student* gender, behavior, FARM. *Teacher* gender, efficacy, proportion of class referred. *School* suspension rate.	*Student* ethnicity. *Teacher* ethnicity, education, experience, burnout. *School* mobility rate, FARM, enrollment, organizational health.	*Strengths*: large sample size, considered nesting of students within teachers and schools, broad range of teacher characteristics. *Limitations*: aggregation bias (teacher school culture beliefs), student achievement not considered.

Appendix H

Quantitative Research on Predictors of Referral to Special Education

Study	Sample Size (*N*)	Data Source	Data Analysis	Level of Independent Measures	Results		Strengths and Limitations
					Significant	Not Significant	
Abidin & Robinson (2002)	90 students 30 teachers	Selected Students	Multiple Regression	Student Teacher	*Student* behavior, academic competence.	*Student* gender, ethnicity, age, FARM. *Teacher* stress.	*Limitations*: sample size, generalizability, limited student and teacher characteristics, student achievement not considered.
Egyed & Short (2006)	106 teachers	Scripted Scenario	ANOVA	Teacher	*Teacher* burnout.	*Teacher* efficacy, training, experience.	*Limitations*: sample size, generalizability, limited teacher characteristics, not considered (student characteristics, student achievement).
Goodman & Webb (2006)	958 students	School Records	Chi-square	Student	*Student* LEP.	*Student* gender, ethnicity.	*Limitations:* generalizability, limited student characteristics, not considered (teacher characteristics, student achievement, student behavior).
Hill, Baldo & D'Amato (1999)	84 teachers	Scripted Scenario	Discriminant Analysis	Student Teacher		*Teacher* efficacy, tolerance, self-concept, locus of control.	*Limitations*: small sample size, all female teacher sample, generalizability, limited student and teacher characteristics, student achievement not considered.

Quantitative Research on Predictors of Referral to Special Education (continued)

Study	Sample Size (*N*)	Data Source	Data Analysis	Level of Independent Measures	Results Significant	Results Not Significant	Strengths and Limitations
Pas, Bradshaw, Hershfeldt, & Leaf (2010)	9795 students, 491 teachers, 31 schools	School Records	Multilevel Logistic Regression	Student Teacher School	*Student* gender, ethnicity, behavior, FARM. *Teacher* proportion of class referred.	*Teacher* gender, ethnicity, education, experience, efficacy, burnout. *School* mobility rate, suspensions, FARM, enrollment, organizational health.	*Strengths*: large sample size, considered nesting of students within teachers and schools, broad range of teacher characteristics. *Limitations*: aggregation bias (teacher school culture beliefs), student achievement not considered.
Schwartz, Wolfe, & Cassar (1997)	65 teachers	Videotape Student Interview	Multiple Regression	Student Teacher	*Student* emotional and behavioral functioning. *Teacher* locus of control, self-esteem (pre-service teachers only).		*Strengths*: data source allowed all participants to view the same naturalistic student responses and behaviors, counterbalanced presentation. *Limitations*: sample size, generalizability, pre-service teachers were half of the sample, limited student and teacher characteristics, student achievement not considered.
Sciutto, Nolfi, & Bluhm (2004)	199 teachers	Scripted Scenario	ANCOVA Pearson *r*	Student Teacher	*Student* gender. *Teacher* referral history.	*Student* ADHD symptom type. *Teacher* gender, experience, ADHD knowledge.	*Strengths*: random assignment. *Limitations*: generalizability, limited student and teacher characteristics, student achievement not considered.

Quantitative Research on Predictors of Referral to Special Education (continued)

Study	Sample Size (*N*)	Data Source	Data Analysis	Level of Independent Measures	Results		Strengths and Limitations
					Significant	Not Significant	
Wallingford & Prout (2000)	16, 379 students	School Records	Chi-square	Student	*Student* summer birth date (age 5 to 7).		*Strengths*: large sample size. *Limitations*: limited student characteristics, not considered (student behavior, student achievement, teacher characteristics).

Note. ADHD = Attention Deficit Hyperactivity Disorder; FARM = Receiving Free and Reduced Meals; LEP = Limited English Proficient; SES = Socioeconomic Status; SPED = Eligible for Special Education.

Appendix I

Measures for Predicting Student Problem-Solving Team Referral

Measure	Source	Description
Outcome		
Student Referral	STFs for 2008-2009	Student referral to a problem-solving team. Categorical coding, 1 = IC Teams; 2 = CS Teams; 3 = No Referral.
Student Predictors		
Sex	Student roster for 2008-2009	Student sex. Dummy coded, 0 = Female, 1 = Male.
Race/Ethnicity	Student roster for 2008-2009	Student race/ethnicity as Caucasian, African American, Hispanic, Asian/Pacific Islander, or Unspecified/Other. Dummy coded, 0 = No, 1 = Yes with Caucasian as the referent group.
Young for Grade	Student roster for 2008-2009 and district regulations for age of entry into kindergarten.	Student age in years on the first day of the 2008-2009 academic year is less than the minimum expected for grade level. Dummy coded, 0 = No, 1 = Yes.
Old for Grade	Student roster for 2008-2009 and district regulations for age of entry into kindergarten.	Student age in years on the first day of the 2008-2009 academic year exceeds the minimum expected for grade level by more than one year. Dummy coded, 0 = No, 1 = Yes.
New to District	Student roster for 2007-2008 and 2008-2009.	Student was not enrolled during 2007-2008. Dummy coded, 0 = No, 1 = Yes.
Special Education	Student roster for 2007-2008	Student received special education during 2007-2008. Dummy coded, 0 = No, 1 = Yes.
FARM	Student roster for 2008-2009	Student qualified for free or reduced price meals in 2008-2009. Dummy coded, 0 = No, 1 = Yes.
ESOL	Student roster for 2008-2009	Student identified as a second language learner in 2008-2009. Dummy coded, 0 = No, 1 = Yes.
Reading	Student grades for 2008-2009	First quarter reading grade in 2008-2009. Standardized within marking metric (mean = 0, standard deviation = 1).
Writing	Student grades for 2008-2009	First quarter writing grade in 2008-2009. Standardized within marking metric (mean = 0, standard deviation = 1).

Measure	Source	Description
Math	Student grades for 2008-2009	First quarter math grade in 2008-2009. Standardized within marking metric (mean = 0, standard deviation = 1).
Concentration	TRSB for 2007-2008	Student attention and diligence to task in 2007-2008. Standardized mean composite of 8 TRSB items (mean = 0, standard deviation = 1).
Externalizing	TRSB for 2007-2008	Student engagement in disruptive, defiant, or acting out behaviors in 2007-2008. Standardized mean composite of 8 TRSB items (mean = 0, standard deviation = 1).
Internalizing	TRSB for 2007-2008	Student engagement in shy, anxious, or withdrawn behaviors in 2007-2008. Standardized mean composite of 8 TRSB items (mean = 0, standard deviation = 1).
Closeness	TRSB for 2007-2008	Student shares a caring, supportive relationship with the teacher in 2007-2008. Standardized mean composite of 4 TRSB items (mean = 0, standard deviation = 1).
Conflict	TRSB for 2007-2008	Student shares a contentious or unpredictable relationship with the teacher in 2007-2008. Standardized mean composite of 4 TRSB items (mean = 0, standard deviation = 1).
Teacher Predictors		
Sex	Teacher roster for 2008-2009	Teacher sex. Dummy coded, 0 = Female, 1 = Male.
Race/Ethnicity	Teacher roster for 2008-2009	Teacher race/ethnicity as Caucasian or non-Caucasian. Dummy coded, 0 = No, 1 = Yes with Caucasian as the referent group.
Age	Teacher roster for 2008-2009	Teacher age in years on the first day of the 2008-2009 academic year. Standardized (mean = 0, standard deviation = 1).
Master's or Higher	TSR for 2008-2009	Teacher holds a Master's degree or higher. Dummy coded, 0 = No, 1 = Yes.
Years Teaching	TSR for 2008-2009	Teacher teaching experience in years as 1 to 5 years, 6 to 10 years, more than 20 years. Dummy coded, 0 = No, 1 = Yes with 1 to 5 years as the referent group.
Years at School	TSR for 2008-2009	Teacher teaching experience at current school in years as 1 to 5 years, 6 to 10 years, more than 20 years. Dummy coded, 0 = No, 1 = Yes with 1 to 5 years as the referent group.

Measures for Predicting Student Problem-Solving Team Referral (continued)

Measure	Source	Description
Efficacy	TSR for 2007-2008	Teacher beliefs in the ability to adapt to and support students with learning and behavioral challenges in 2007-2008. Standardized mean composite of 16 TSR items (mean = 0, standard deviation = 1).
Collaboration	TSR for 2007-2008	Teacher perceptions in 2007-2008 that school staf coordinate with and support each other. Standardized mean composite of 10 TSR items (mean = 0, standard deviation = 1).
Job Satisfaction	TSR for 2007-2008	Teacher loyalty and appreciation for the school in 2007-2008. Standardized mean composite of 4 TSR items (mean = 0, standard deviation = 1).
Instructional Practices	TSR for 2007-2008	Teacher application of effective instructional principles and practices in 2007-2008. Standardized mean composite of 18 TSR items (mean = 0, standard deviation = 1).

Note. STF = Systems Tracking Form. FARM = Free or reduced price meals. ESOL = English as a second or other language. TRSB = Teacher Report on Student Behavior. TSR = Teacher Self Report.

Appendix J

Instructional Consultation Teams Systems Tracking Form

DISTRICT: _____ SCHOOL: _____ FACILITATOR: _____.

INSTRUCTIONAL CONSULTATION SYSTEM TRACKING FORM 2008 to 2009

Student Name/Student School ID Number (optional) (SHOULD NOT BE SUBMITTED TO LAB FOR IC TEAMS)	IC Team Student Code Number	Gr.	Requesting Teacher	Case Manger	Request Date	Date of Contract	Date (s) of Prob.ID: General Concern	Date(s) of Instructional Assessment	Type of Concern	Date(s) of Interven./ Design/ Implem.	Date(s) of Interven. Eval.	Date of Closure/ Reason for Closure
	1											
	2											
	3											
	4											
	5											
	6											

INSTRUCTIONS: Use this document to record the information for all students who are being served through the IC Team. The IC Team student code number that is listed in the second column on this form is the student code number that should be used for the same student on the SDF and the Summary of IC Team Cases form. The student's name and/or school ID number can be listed in the first column *for school purposes only.* (Note: the student's school ID number is optional.) The column listing the student's name/ student school ID number should be folded over or covered before this form is copied and sent out of the building for IC Team evaluation purposes. *PLEASE DO NOT SEND ANY DOCUMENTS WITH STUDENT NAMES ON THEM OUT OF THE SCHOOL FOR IC EVALUATION PURPOSES, ONLY SEND STUDENT CODES.*

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Appendix K

Child Study Teams Systems Tracking Form

DISTRICT:_____   SCHOOL:_____   FACILITATOR:_____.

SUMMARY OF OTHER CASES NOT SERVICED BY ICT 2008-2009

Stud Name/ School ID Number	Stud. Eval. Code	Gr.	Referral Date	PreReferral Team	Referral Source	Type of Concern	Race	Sex	ESL	Existing Disability	Referred for Eval	Found Eligible	What Disability?
	A			PST SST Other: CS	Parent Teacher Other____	Math Read WL Beh Sp/Lang Other____	AA A C H N Other____	M F	Y N	Y N	Y N	Y N	
	B			PST SST Other: CS	Parent Teacher Other____	Math Read WL Beh Sp/Lang Other____	AA A C H N Other____	M F	Y N	Y N	Y N	Y N	
	C			PST SST Other: CS	Parent Teacher Other____	Math Read WL Beh Sp/Lang Other____	AA A C H N Other____	M F	Y N	Y N	Y N	Y N	
	D			PST SST Other: CS	Parent Teacher Other____	Math Read WL Beh Sp/Lang Other____	AA A C H N Other____	M F	Y N	Y N	Y N	Y N	

INSTRUCTIONS: Use this document to record the information for all students who are being served through school teams other than the IC Team and those students referred for special education evaluation. The IC Team student code that is used on this sheet is an alphabetic letter in order to distinguish these students from students served through the IC Team. The student's name and/or school ID number can be listed in the first column *for school purposes only*. The column listing the student's name/ student school ID number should be folded over or covered before this form is copied and sent out of the building for IC Team evaluation purposes. *PLEASE DO NOT SEND ANY DOCUMENTS WITH STUDENT NAMES ON THEM OUT OF THE SCHOOL FOR IC EVALUATION PURPOSES, ONLY SEND STUDENT CODES.*

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Appendix L

Teacher Report on Student Behavior (TRSB): Behavior Scale Items

Scale	Item
Concentration	1. Easily distracted (reverse score)
	2. Accomplishes assignments independently
	3. Eager to learn
	4. Works to overcome obstacles in schoolwork
	5. Says things like "I can't do it" when work is difficult (reverse score)
	6. Stays on task
	7. Pays Attention
	8. Learns up to ability
Externalizing	1. Defies teachers or other school personnel
	2. Argues or quarrels with others
	3. Teases or taunts others
	4. Takes others property without permission
	5. Is physically aggressive or fights with others
	6. gossips or spreads rumors
	7. Is disruptive
	8. Breaks Rules
Internalizing	1. Interacts with teachers (reverse score)
	2. Seems sad
	3. Makes friends easily (reverse score)
	4. Withdrawn - doesn't get involved with others
	5. Seems anxious or worried
	6. Shy or timid around classmates or adults
	7. Socializes or interacts with classmates (reverse score)
	8. Is a loner
Response Categories	
Never/Almost Never = 0, Sometimes = 1, Often = 2, and Very Often = 3	

Appendix M

Teacher Report on Student Behavior (TRSB): Student-Teacher Relationship Scale Items

Scale	Item
Closeness	1. I share a warm caring relationship with this child
	2. If upset, this child will seek me out for support
	3. This child values his relationship with me
	4. This child spontaneously shares his feelings and experiences with me
Conflict	1. This child and I always seem to be struggling with each other
	2. This child's feelings toward me can be unpredictable or change suddenly
	3. This child is sneaky or manipulative with me
	4. Dealing with this child drains my energy
Response Categories	
Definitely Does Not Apply = 0, Not Really = 1, Neutral, Not Sure = 2, Applies Somewhat = 3, and Definitely Applies = 4	

Teacher Self-Report (TSR) Scale Items

Scale	Item
Efficacy	1. How much can you do to adjust your lessons to the proper level for individual students? 2. To what extent can you gauge student comprehension of what you have taught? 3. To what extent can you craft good questions for your students? 4. To what extent can you use a variety of assessment strategies? 5. To what extent can you provide an alternative explanation or explanation when students are confused? 6. How well can you implement alternative teaching strategies in your classroom? 7. How much can you do to increase the achievement of a student who has a specific learning disability? 8. How much can you do to increase the academic achievement of a student whose parents have a limited educational background? 9. How much can you do to "catch up" a student who comes to you reading two years below grade level? 10. How much can you do to increase the achievement of a student from a disadvantaged family background? 11. Within your classroom, to what extent can you help promote learning in students who receive special education services? 12. How much can you do to improve the academic performance of a student whose home environment lacks structure and discipline? 13. How much can you do in your classroom to improve the learning of a student with emotional and/or behavioral problems? 14. Within your classroom, how much can you help English Language Learners (ELL) improve their academic performance? 15. If a student in your class has parents who are not involved in the academic process, how much can you do to help this child learn? 16. How much can you do to increase the achievement of a student with attention problems?
Response Categories *Nothing/Not At All = 1, Very Little = 2, Some = 3, Quite a bit = 4, and A Great Deal = 5*	
Job Satisfaction	1. I like working in this school 2. I would recommend this school to parents seeking a school for their child. 3. I usually look forward to each working day at this school. 4. I feel loyal to this school.
Response Categories *Strongly Disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly Agree = 5*	

Teacher Self-Report (TSR) Scale Items (continued)

Scale	Item
Collaboration	1. In our school, teachers are expected to work with specialists and other teachers to resolve problems.
	2. In our school, teachers formally schedule time to collaborate about teaching and learning practices.
	3. Specialists (e.g., ESOL teachers, special educators, reading teachers) and classroom teachers plan together for students they teach in common.
	4. Teachers are on their own to solve classroom problems in this school.
	5. In this school, it is seen as a sign of weakness if a teacher asks for help.
	6. Teachers are uncomfortable asking for help when they have a behavior problem in their classroom.
	7. Teachers in this school work together to design instruction.
	8. Teachers in this school coordinate instructional goals across grade levels.
	9. Teachers in this school consult with each other to improve their own classroom management.
	10. I am more likely to ask a colleague to work with me on my instruction than to ask them to work with the student.
Instructional Practices	1. I assess the level of challenge an academic task will provide this student.
	2. I take the time to assess this student's prior knowledge and skills before teaching a lesson.
	3. I preview reading materials to ensure that this student will be able to read text with at least 93% level of accuracy.
	4. I monitor the student's understanding or the content of a skill during activities and make adjustments accordingly.
	5. I make adjustments during lessons based on this student's understanding of the content or skill.
	6. I walk around to give immediate and specific feedback to this student while he or she is practicing a new skill.
	7. I prepare practice exercises for this student so that he or she knows at least 75% of the material before starting the task.
	8. For critical skills, I ensure that this student's practice is continued to the point of mastery.
	9. I ensure that this student's engagement is high during independent work activities.
	10. I do more than the school system and curriculum requires to assess this student's performance on classroom tasks.
	11. I assess this student to pinpoint the most important instructional needs.
	12. I set short-term goals for this student.
	13. I collect data on this student to monitor progress toward short-term goals.
	14. I flexibly group this student with other students by skill or objective.
	15. I assess this student's academic skills in the subject areas in which the behaviors are occurring.
	16. I define this student's behavior in specific and observable terms.
	17. I analyze what happens immediately before and after this student's behavior.
	18. I graph data about this student's increase in appropriate behaviors.
Response Categories	
Never = 1, Rarely = 2, Sometimes = 3, Often = 4, Always = 5	

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