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Exploring Social, Emotional, and Behavioral Screening Approaches in U.S. Public School Districts

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Using a nationally representative sample of U.S. public school districts, we explored the current landscape of social, emotional, and behavioral (SEB) approaches and their impact on behavioral outcomes. Data suggest SEB screening is the exception rather than the rule, with most districts reporting that students are referred to an internal support team when SEB concerns arise. Districts more likely to report SEB problems were identified and supported internally when they had elementary SEB programs, were located in urban areas, and had higher socioeconomic status levels. District administrators who reported that SEB problems were identified and addressed internally, including use of universal screening procedures, reported the highest levels of knowledge about their SEB approach as well as willingness to change their practices.

KEYWORDS: behavioral, emotional, school-based screening, social

Social, emotional, and behavioral (SEB) disorders such as conduct problems, attention deficit, anxiety, and depression are among the most prevalent health conditions for children and adolescents (Perou et al., 2013). Urgency in improving behavioral health services accessibility has been noted (Splett et al., 2018), with concerns such as costs to society estimated at over \$200 billion, substantial proportions of youth not receiving necessary services, and increasing incidence rates with decreasing federal support (e.g., Hoagwood et al., 2017; Merikangas et al., 2011; Olfson et al., 2015; Perou et al., 2013). Schools have been advocated as a mechanism for improving behavioral services accessibility, providing a place for early identification of SEB issues and service provision (National Academies of Sciences, Engineering, and Medicine, 2019). However, rather than serving a role in identification for prevention and early intervention, U.S. public schools have mainly employed reactive models that wait until student problems compound to a point necessitating intensive interventions such as specialized programs or out-of-school placements (Stiffler & Dever, 2015). To date, little is known about how schools nationally have adjusted to a shift in expectation for responsibilities that include proactive SEB identification procedures such as screening. Establishing and understanding the landscape of U.S. public school district approaches to identifying and supporting students' SEB needs serves as the purpose of this article.

History and Rationale for SEB Screening in Schools

Given that the vast majority of children and adolescents in the United States attend schools, schools can offer an advantageous setting for identifying and supporting student SEB needs (National Academies of Sciences,

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Engineering, and Medicine, 2019; Splett et al., 2018). In fact, federal recommendations and legislation have promoted a shift in school services from reactive to proactive identification of SEB needs. For example, the President's Commission on Excellence in Special Education recommended that universal screening be conducted in the early grades to identify and offer support to students struggling with both academic and behavioral concerns, before these challenges affect other educational outcomes (U.S. Department of Education Office of Special Education and Rehabilitative Services, 2002). Federal legislation, such as the 2004 reauthorization of the Individuals With Disabilities Education Act, also promotes early identification and intervention. In addition, various pieces of proposed legislation, such as the Mental Health in Schools Act of 2015 (H.R. 1211), represent attempts to extend these goals. This resolution aimed to help school districts establish school-based comprehensive mental health programs that encourage early identification of students with SEB needs and provide related training for school personnel.

The underlying foundation for screening is to serve a proactive capacity in which problems are identified early so that intervention supports can be provided before the problems become more intractable and necessitate more intensive services (Lane et al., 2020). Screening in academic domains (e.g., reading) has a long history in schools as a proactive purpose to providing supplemental supports, with recent decades bringing attention to SEB screening as equally relevant given the connections between behavioral and academic success (Chafouleas et al., 2010). That is, behavioral concerns that are not addressed proactively and instead allowed to escalate result in consequences that can lead to long-term negative outcomes such as lower achievement, dropout, and involvement in juvenile justice systems (e.g., Cholewa et al., 2018; Chu & Ready, 2018; Wolf & Kupchik, 2017). However, screening for SEB risk can take many forms based on instrumentation, procedures, assessment constructs, and population. Universal screening means that standard procedures are applied to all students in a given population (e.g., early elementary grades, Grade 7 students), with the intent that each student has the opportunity to be assessed for risk. Typically, the measures are brief, such as a short rating scale or standard teacher nomination procedures, and followed by additional assessments to confirm risk status and determine direction for intervention. In contrast, a targeted screening approach may use similar instrumentation and procedures but generally means that only select groups of students are included in risk assessment. Although evidence to support one screening approach over another is not yet available, universal screening approaches have been advocated as an attractive alternative to teacher referral approaches, which may be too dependent on teacher knowledge, attitudes, and beliefs, as well as reliant on behaviors that are observable to adults (Lane et al., 2010). Some evidence suggests that scores on brief SEB screening measures administered at the beginning of the school year may significantly predict both behavioral and academic outcomes in the spring (Eklund et al., 2017; Menzies & Lane, 2012), thereby suggesting SEB screening may serve as an important component to preventive frameworks.

Current Status of SEB Screening in Schools

Despite general support for SEB screening in schools, existing research lacks evidence of widespread use (Glover & Albers, 2007). For example, a 2004 study commissioned by the Annenberg Public Policy Center found that fewer than 10% of secondary schools conducted mental health screening for the majority of students, and roughly 26% conducted no screening at all (Romer & McIntosh, 2005). Approximately 10 years later, Bruhn et al. (2014) surveyed a convenience sample of school and district administrators (DAs), which revealed that the vast majority of respondents from K–12 schools reported no use of SEB screening. When asked for the primary reasons SEB screening was not conducted, respondents most frequently indicated that they did not (a) know SEB screening existed, (b) have sufficient financial resources to conduct SEB screening, or (c) have access to appropriate SEB screening tools (Bruhn et al., 2014).

The aforementioned studies suggest underutilization of SEB screening in the United States; however, the body of work is limited in three primary ways. First, existing knowledge has been built on the use of convenience or small area samples. Although such studies provide insight into the practices of particular school districts or states, results do not describe approaches to identifying and supporting student SEB needs throughout the United States. Because school districts are locally managed and given limited state guidance regarding SEB screening (Briesch et al., 2019), it is uncertain if SEB approaches in one district, state, or region occur in others.

Second, prior survey studies have generally not investigated what schools are doing in lieu of SEB screening. Existing work draws a dichotomy between schools that conduct SEB screening and those that do not, without exploring alternatives that schools might use to identify and support students with SEB needs. For example, schools that do not elect to use a standard screening approach, either universal or select, may be engaged in an approach that involves early SEB intervention efforts targeted toward an individual student. These approaches assume the school's role in addressing needs may include focused efforts such as individual student referral to an internal support team to develop an intervention plan or encourage teachers to independently develop and implement an intervention plan before referring the student for assistance. These approaches may be common given that the majority of states across the country either recommend or mandate the use of prereferral teams, which provide consultative assistance to teachers when student concerns in the classroom are encountered (Truscott et al., 2005). However, work in SEB domains has more heavily focused on a limited range of behaviors (e.g., disruptive behaviors) and has not specifically investigated the role of SEB screening data in the process toward improved outcomes. In addition, these efforts are generally directed toward the individual student, potentially losing the opportunity to connect a full continuum of prevention strategies across school-wide, class-wide, and individual levels.

Third, extant work has focused on whether screening takes place without understanding the assessment choices in relation to other contextual features such as state and local policies. For states that mandate that districts have SEB standards, evaluation may be an included component, which may advance use of SEB screening approaches. As detailed by Aarons et al. (2011), both inner and outer contexts can influence use of evidence-informed practices. The school itself (i.e., inner context) must attend to both individual adopter (e.g., knowledge, willingness) and intraorganizational (e.g., climate, leadership) characteristics. Yet, particularly for SEB problems, the school is also influenced by the outer context, which can include factors such as consumer advocacy, interorganizational networks, state and district policy, and funding support. Thus, information about school assessment practices alone does not create a complete picture of SEB screening practices, contextual features of the choices, and the connection between SEB approaches and student outcomes.

Purpose of the Study

Although calls have been made to increase schools' role in SEB screening, existing studies have suggested that rates of SEB screening in schools are low (Bruhn et al., 2014; Romer & McIntosh, 2005). However, extant work is limited, given sampling and a lack of supporting information to understand contextual features. The primary purpose of this study was to explore the national landscape of approaches to identifying and supporting students' SEB needs in U.S. public school districts across various stakeholder groups, including DAs. Secondary purposes of the study included exploration of differences between SEB approaches used, and whether SEB approaches result in differences in behavioral outcomes or perceived usability. That is, before significant investments to enhance uptake of SEB screening are undertaken, it is important to understand not only the current national landscape of school-based approaches to identifying and supporting student SEB needs but also the influences on approaches taken. Together, the three research questions were as follows:

Research Question 1: As reported by DAs, what are the current approaches to identifying and supporting student SEB concerns in schools across the United States?
Research Question 2: Do patterns in use of SEB approaches vary based on student demographics, district characteristics, use of SEB standards and programs, and/or perceived usability of the current SEB approach?
Research Question 3: Do districts that use more proactive approaches to identifying and supporting students' SEB needs differ from districts that use less proactive approaches with regard to behavioral outcomes or usability?

Method

Participants and Sampling

The nationally representative sample of U.S. public school districts identified for this study emanated from the 2013–2014 Common Core of Data (CCD) Local Education Agency (School District) universe. Superintendents from the 12,470 districts in our sample frame received mailed invitation letters between December 2015 and August 2016 introducing the project, providing brief explanations of procedures, and offering study findings as a participation incentive. Invitations were followed by phone calls and emails that included the link to the online survey. In this process, some districts were deemed ineligible (i.e., duplicates, districts closed or consolidated, charter school districts), leaving 12,315 eligible districts. From these, 1,330 district-level administrators (superintendents [60%], assistant superintendents/pupil services/special education/curriculum directors [32%], other DAs [8%]) completed the DA Survey, resulting in an unweighted response rate of 10% ([number of responding units]/[number of eligible units + number of sample units with eligibility not determined]; see Petroni et al., 2014). Although the low response rate may suggest concern regarding representativeness of the sample, it is important to note that (a) serious effort (minimum of six attempts) was made to contact selected respondents including prenotification by mail, an email invitation, a mail reminder including a hard copy of the instrument and return envelope, three reminder emails, and a phone call reminder and (b) sample quality should be evaluated by comparing the sample characteristics with the population characteristics. Table 1 provides the distribution of district characteristics as they occur in the population, final sample, and final sample adjusting for nonresponse. The table shows that the unweighted study sample characteristics closely match the population of U.S. school districts. Weights ranging from 0.45 to 2.75 were applied to the final data set to adjust for nonresponse across census region, urbanicity, and district size. Based on sample characteristics and minimal use of weights, we do not observe patterned nonresponse and consider the sample representative of the population.

Of the 1,330 participating school districts, as in the population of U.S. public school districts, the largest number were located in the Midwest (37.35%), followed by the South (24.82%), Northeast (20.41%), and West (17.41%). The vast majority of districts were nonurban (92.30%). In addition, most districts were moderate in size (i.e., between 1,001 and 5,000 students: 41.16%) or small (i.e., 100–500 students: 24.48%). Less than 5% of the sample (4.4%) included large districts (i.e., 15,001 or more students). Most participating school districts received Medicaid funding to support students with disabilities (72.37%). On average, 14.77% of students in a district received special education services (standard error [*SE*] = 0.35) and 64.89% of the students with individualized education plans learned in least-restrictive

Table 1
Population and Survey Sample Characteristics of Public School Districts in the United States

Characteristic	Population (%)	Sample (%)	Final Weighted Sample (%)
Urbanicity			
Large city	1.49	1.50	1.48
Small to midsize city	4.52	5.11	4.52
Suburb	24.46	22.63	24.47
Town	19.55	20.38	19.54
Rural	49.99	50.38	49.98
Census region			
Northeast	20.41	23.76	20.41
Midwest	37.35	37.59	37.35
South	24.82	23.68	24.82
West	17.41	14.96	17.41
Number of students			
100–500	24.49	22.33	24.48
501–1,000	18.72	18.72	18.71
1,001–5,000	41.19	42.41	41.16
5,001–15,000	11.19	11.28	11.22
150,001–highest	4.42	5.26	4.44

environments (LRE) 80% or more of the day (SE = 0.49). In addition, 11.68% of the students were Hispanic (SE = 0.54), and 8.09% were Black (SE = 0.48; see Table 3). Table 1 provides summaries of the population and district characteristics for the final survey sample with and without weights. Demographic characteristics for the DA Survey respondents appear in Table 2, and additional district characteristics used in analyses are in Table 3. Complete information regarding the project methodology, including the survey instruments, appears in Marcy et al. (2018) and the Supplemental Appendix in the online version of the journal.

Measures

The overall project incorporated survey data with existing administrative data sources, including 2013–2014 National Center for Education Statistics CCD, 2013–2014 Stanford Education Data Archive (SEDA), and district-procured special education data. Descriptions of each data source are provided next.

District Administrator Survey

The research team engaged in an iterative process to develop the DA Survey items. First, an expert panel consisted of SEB health and school-based scholars and practitioners reviewed draft survey items. Next, our instrument

Table 2
District Administrators: Respondent Characteristics

Characteristic	*n*	%
Gender (female)	574	46.76
Race		
American Indian/Alaskan Native	25	2.38
Black/African American	47	3.98
White	1,119	93.87
Other/unspecified	19	1.60
Hispanic origin	36	3.16
Highest degree		
Bachelor's degree	12	1.04
Master's degree	206	17.59
Master's plus/certificate of advanced graduate study	663	53.80
Doctoral degree (PhD, EdD, PsyD)	330	26.61
Other/unspecified degree	11	0.96
Position before becoming administrator		
Teacher	893	73.82
Related services provider	429	34.43
Administrator	203	16.68
Other position	130	10.76
Current position		
Superintendent		60.00
Assistant superintendent or director (pupil service/ special education/curriculum)		32.00
Other/unspecified		8.00
Number of years in current position, *M* (*SE*)	5.54	0.15
Number of years in education, *M* (*SE*)	25.77	0.26

Note. Table includes unweighted frequencies, weighted percentages, and weighted means and standard errors. The "Other/unspecified" race category includes district administrators, who selected the Asian, Asian Indian, Native Hawaiian, Other Pacific Islander, and/or Other/unspecified race options (due to small numbers of individuals choosing these responses). The "Other/unspecified" degree category includes district administrators, who reported earning a high school diploma/equivalent or Other/unspecified degree, due to small numbers of individuals choosing these responses. For position before becoming an administrator: "Teachers" include both classroom teachers and unified arts teachers (music, art, physical education, health, library, technology); "Related services providers" consist of school counselors, school psychologists, school social workers, special education teachers, and speech-language pathologists; "Administrators" represent both district and school administrators; and "Other position" suggests the respondent worked at the State Department of Education or an Other/unspecified position.

was subjected to cognitive testing to ensure that respondents would comprehend, process, and respond to the survey items in a manner consistent with the researchers' intent. Finally, a field pretest was conducted to ensure that the survey instrument and data collection process functioned optimally.

Table 3
District and Student Characteristics

Characteristic	*n*	%
Census division[a]		
Northeast	316	20.41
Midwest	500	37.35
South	315	24.82
West	199	17.41
Urbanicity[b]		
Urban	107	7.70
Nonurban	1,192	92.30
District size[a]		
100–500 students	297	24.48
501–1,000 students	249	18.71
1,001–5,000 students	564	41.16
5,001–15,000 students	150	11.22
15,001 or more students	70	4.44
Medicaid funding[c]		
District received Medicaid funding for students with disabilities	894	72.37
	M	*SE*
Standardized testing[b]		
Grade 3 English/Language Arts	209.22	0.45
Grade 3 Mathematics	230.85	0.36
Grade 8 English/Language Arts	265.84	0.40
Grade 8 Mathematics	284.34	0.49
District per-pupil expenditures[b]	12,756.78	131.20
District student-teacher ratio[b]	14.97	0.11
District socioeconomic status[b]	0.10	0.03
	M (%)	*SE* (%)
Percentage of district students receiving special education services[d]	14.77	0.35
Percentage of district students identified with EBD[d]	1.47	0.07
Percentage of district students with IEPs in least-restrictive environment 80% or more of the day[d]	64.89	0.49
Percentage of district students that are ELLs[b]	4.21	0.24
Percentage of district students receiving free lunch[b]	37.89	0.58
Percentage of district students that are Black[b]	8.09	0.48
Percentage of district students that are Hispanic[b]	11.68	0.54

Note. Table includes unweighted frequencies, weighted percentages, and weighted means and standard errors. EBD = emotional disability/emotional behavioral disorder. IEP = individualized educational plan. ELLs = English language learners.
[a]Variables originated in the National Center for Education Statistics Common Core of Data.
[b]These variables came from the Stanford Education Data Archive.
[c]Researchers collected these data with the DA Survey.
[d]Data were collected via requests for information from individual districts.

The DA Survey included questions about (a) districts' current academic and SEB standards and programs for elementary and secondary grades, (b) DAs' perceptions of the purpose and value of SEB screening, (c) DAs' indication of their district's primary approach to identifying and supporting SEB needs of students as well as insights regarding the usability of that approach and perceptions of the ideal approach, and (d) DA demographics.

This study did not incorporate data from all pieces of the DA Survey, and thus, we provide brief summary of only those included variables here.

The first set of variables provided information on district adoption of elementary and secondary SEB standards and programs, as well as the sources of those decisions. Next, information was included regarding our primary outcome of interest: districts' current primary approach to identifying and supporting students' SEB needs (i.e., referred to herein as *current SEB approach*). Six specified approach options were randomly provided, to minimize response order effects, along with options for other approaches, no approach, or a preference to not specify. The first option was *Screening for All*, meaning that districts complete a brief SEB screening measure for all students and refer any student falling outside the typical range for assistance. The second choice was *Familiar Adult Nomination* in which a familiar adult (e.g., teacher) nominates those students exhibiting SEB problems and then completes a screening measure only for those nominated to determine who gets referred for assistance. The *Internal Referral* approach involves referring students who are exhibiting SEB problems to an internal support team to develop and implement an intervention plan. Fourth, DAs could select *Teacher Intervention*, in which districts encourage teachers to independently develop and implement an SEB intervention plan in the classroom; if the issue does not resolve, teachers then refer the student for additional assistance. *External Referral* entails the referral of students exhibiting SEB problems to an outside consultant or agency for assistance. Two remaining options included the possibilities that districts currently use another SEB approach than the ones described or no approach at all. DAs could also select responses indicating that they did not know which approach their districts used or that they preferred not to answer.

Finally, the DA Survey included the Usability Rating Profile–NEEDS (URP-NEEDS: Chafouleas et al., 2018), an instrument designed to assess the usability of approaches to identifying and supporting students with SEB needs. The URP-NEEDS consists of 24 items and 5 separate subscales (see Table 5). URP-NEEDS items use a 6-point Likert-type rating scale, such that "1" indicates the respondent *strongly disagrees* and "6" suggests they *strongly agree* with the presented statement. The *Knowledge* subscale is the 10-item factor (α = .94), which represents respondents' knowledge of the purpose, goals, and procedures associated with a particular SEB approach, as well as their understanding of how to execute the SEB approach and use the resulting data. The *Willingness to Change* (α = .87) subscale includes four items designed to measure respondents' flexibility with regard to adopting novel SEB practices. The *Feasibility* subscale (α = .86) features four items designed to assess perceptions of the availability of sufficient time and resources to effectively carry out an SEB approach. The *Family-School Collaboration* subscale (α = .78) has three items that assess the degree to which the implemented SEB approach requires cooperation and contact between students' family members/loved ones and school personnel to successfully ameliorate SEB challenges. *External Supports* (α = .73) is the final three-item subscale, which represents the degree to which a given SEB approach requires strong bonds outside of school, in the form of community partnerships and external consultation. Whereas two of the subscales (Family-School Collaboration and External Supports) are slightly below the .80 threshold, we have included them in the analysis because the importance of the constructs warrants inclusion and because the URP-NEEDS measure is built on a history of prior work that establishes the constructs as valid and reliable indicators of usability of different school-based assessment and intervention innovations (see Briesch et al., 2019)

National Center for Education Statistics Common Core of Data

The NCES CCD Local Education Agency (District) Universe Survey is an annually released database that includes data on all public school districts across the United States. This database includes district-level frequencies of students by grade, sex, race/ethnicity, disability, and English language learner status (NCES, 2005). Using the 2013–2014 CCD, we created a Census Region variable based on FIPST code, "an American National Standards Institute [ANSI] state code" (NCES, 2015). We utilized this Census Region variable for both descriptive analyses and multinomial logistic regression modeling. We also developed a coarsened, five-category District Size variable based on the CCD's MEMBER variable, which is "the count of students enrolled on October 1 of the school year," from pre-K to 12th grade (NCES, 2015).

Stanford Education Data Archive

Stanford's Center for Education Policy Analysis created the publicly available SEDA database to gather and disseminate data to improve educational policies and possibilities for students. The database incorporates and decomposes data from districts, schools, communities, geographic areas, and so on, by variables such as grade, race, socioeconomic status (SES), academic subject, and standardized test scores (Fahle et al., 2017). For this study, we used several district-level variables from the 2013–2014 SEDA database, including Grade 3 District Achievement (i.e., averaged English/Language Arts and Mathematics standardized test scores), urbanicity (urban vs. nonurban), per-pupil expenditures, and student-teacher ratio. We also included SEDA's SES variable for the multinomial logistic regression analyses (a composite variable created from income level, percentage of individuals with bachelor's degrees, and poverty, grocery assistance, single parenting, and employment rates; Fahle et al., 2017). We used three aggregate student-level variables for both the multinomial logistic regression and the propensity score analyses: percentage of English language learners and percentages of Black and Hispanic students. Additional SEDA variables used for each analysis are in the appendix.

District-Level Special Education Data

We applied directly to individual states and districts to obtain various special education data for each district in our sample. We requested information for the 2012–2013 academic year regarding the total number of students receiving special education services and, of those students, the total number with a diagnosis of Emotional Disturbance (ED). To facilitate interpretation, we transformed each frequency variable into a percentage variable prior to data analysis (e.g., percentage of students receiving special education services). We also requested the percentages of students with individualized education plans, aged 6 to 21 years, learning in LREs more than 80% of the day (i.e., LRE80). We incorporated all three variables in our descriptive analyses. However, after prescreening the data, we decided not to use the percentage with diagnosis of ED variable for our multinomial logistic regression models due to challenges in obtaining complete and reliable data from states and districts.

Data Analysis

We used three different analysis strategies to address the research questions. First, using descriptive analyses, we explored the current landscape of approaches to identifying and supporting student SEB needs used in school districts across the United States. These analyses also described the presence of various SEB standards and programs (Table 4) as well as DAs' perceptions of the usability of their current SEB approach (see Table 5). As previously noted, weights were applied to the final data set to adjust for nonresponse across census region, urbanicity, and district size, resulting in a nationally representative sample.

To determine student demographics, district characteristics, use of SEB standards, and predicted patterns in use of SEB approaches, we conducted a series of multinomial logistic regression models. With regard to SEB approaches, the survey options describing the current SEB approach were collapsed into three categories, chosen to represent a continuum of recommended practices, from universal screening to internal handling to external referral or no approach. That is, engaging in an approach that allows each student an opportunity to be assessed for SEB risk (i.e., universal screening) aligns with a prevention and early intervention framework proactive in addressing SEB challenges before more intensive individualized supports are required. In contrast, approaches that wait for problems to surface that may be substantive and warrant intervention are considered less preventive. We merged the *Screening for All* and *Familiar Adult Nomination* groups, given that both involve the proactive consideration of all students in a class,

Table 4
District Administrator–Reported Influences on Academic Standards, Social, Emotional, and Behavioral (SEB) Standards, and SEB Programs in Elementary Settings

	Elementary Level		Secondary Level	
Influences on Standards	*n*	%	*n*	%
Academic standards exist	1,284	99.00	1,151	98.36
Building-specific decision	50	3.78	37	3.12
District-wide decision	203	15.50	162	13.69
State mandate	1,029	80.72	952	83.19
SEB standards exist	533	41.10	428	36.88
Building-specific decision	177	32.36	161	37.30
District-wide decision	248	46.83	191	44.75
State mandate	108	20.81	75	17.95
SEB universal programs adopted	745	56.67	468	39.95
Building-specific decision	264	34.93	148	31.93
District-wide decision	443	59.91	288	60.94
State mandate	36	5.16	32	7.13

grade, or school coupled with a brief assessment to inform the choice of subsequent supports. Thus, both rely on adult knowledge and familiarity with a student, and procedures applied to all students in a given population. We joined *Internal Referral* and *Teacher Intervention* groups as both involve the design and implementation of school-based intervention supports to address teacher concerns. That is, both involve internal supports or strategies using existing school resources. Third, we combined the *External Referral* and *No SEB Approach* groups given that both meant that student SEB problems were not being addressed directly by school staff. This grouping yielded 189 districts practicing *Familiar Adult Nomination* or *Screening for All* (FASA), 829 districts employing *Internal Referral* or *Teacher Intervention* (IRTI), and 188 districts utilizing *External Referral* or *No Approach* (ERNO).

Finally, we used propensity score analysis to answer the third research question about differences in behavioral outcomes or usability for districts that use more versus less proactive SEB identification practices. The propensity score is "the conditional probability of receiving the treatment, given the observed covariates" (Rosenbaum, 2002, p. 296). If strong ignorability and the stable unit treatment value assumption are plausible, then propensity score analysis can be used to generate unbiased estimates of treatment effects using observational data (Pan & Bai, 2015). Our goal was to examine the effect of the current SEB approach on behavioral outcomes and usability. For these analyses, we eliminated IRTI to focus on the comparison between the most proactive

Table 5

District Administrator Indications of Primary Current Social, Emotional, and Behavioral (SEB) Approach Used, and Perceptions of the Usability of That Approach

			Usability Rating Profile–NEEDS									
			Knowledge		Willingness		Feasibility		Family/School Collaboration		External Supports	
Choice	*n*	%	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Screening for All	69	5.54	4.21	0.10	4.23	0.11	4.11	0.14	5.01	0.12	4.90	0.11
Familiar Adult Nomination	120	9.81	3.89	0.08	4.12	0.08	3.66	0.10	5.03	0.07	4.79	0.09
Internal Referral	699	54.70	3.86	0.04	4.16	0.03	3.74	0.04	5.11	0.03	4.81	0.03
Teacher Intervention	130	10.14	3.82	0.09	4.25	0.08	3.73	0.10	5.02	0.07	4.61	0.09
External Referral	153	12.11	3.53	0.08	3.92	0.07	3.50	0.08	4.98	0.07	4.95	0.06
Other	95	7.69	3.11	0.23	3.87	0.21	3.19	0.27	5.25	0.20	4.89	0.19

Note. Table includes unweighted frequencies, weighted percentages, and weighted means and standard errors. The items on all five SEB usability subscales had the same 6-point Likert-type response scale: "1" suggests the respondent *strongly disagreed* with the provided statement, whereas "6" indicates that the respondent *strongly agreed* with the statement.

SEB approach (FASA) and the least proactive SEB approach (ERNO). Thus, we compared the districts that reported using standard procedures applied to all students in a population (FASA: N = 189) to the districts that reported that they refer students externally or who have no approach (ERNO: N = 188).

Results

Research Question 1: Current Approaches to Identifying and Supporting Student SEB Concerns

Nearly all of the districts in our sample had academic standards at both the elementary (99.00%) and the secondary grade levels (98.36%), and most DAs indicated that state mandates had the greatest influence over these standards (80.72% and 83.19%, respectively). In contrast, fewer than half of these districts had SEB standards in elementary (41.10%) and secondary settings (36.88%)—more districts had adopted SEB programs (56.67% and 39.95%, respectively) than SEB standards. When SEB standards and/or programs were reported, DAs were most likely to indicate that this was either a district-wide (SEB standards: 46.83%; SEB programs: 59.91%) or building-specific (SEB standards: 32.36%; SEB programs: 34.93%) decision as opposed to a state mandate (SEB standards: 20.81%; SEB programs: 5.16%; see Table 4).

With regard to primary district-level approach to identifying and supporting student SEB needs, the majority of DAs reported utilizing *Internal Referral* (54.70%), followed by *External Referral* (12.11%), *Teacher Intervention* (10.14%), *Familiar Adult Nomination* (9.81%), and *Other* approaches to SEB identification (7.69%). Only 69 DAs reported use of *Screening for All* (5.54%) in their districts. Overall, DAs reporting that their district's primary current SEB approach involving *Screening for All* tended to report higher ratings of knowledge, willingness to change, and feasibility than DAs reporting other approaches (see Table 5).

Research Question 2: Patterns in Use of SEB Approaches

As described above, to examine variables related to district-level approaches for the identification and support of student SEB needs, we investigated three categories of approaches: standard procedures applied to all students in a population (FASA = Screening for All + Familiar Adult Nomination), internally managed identification methods (IRTI = Teacher Intervention + Internal Referral), and externally managed or absent processes (ERNO = External Referral + No Approach). These three techniques represented the discrete categories for our outcome variable of interest: current district-level SEB approach.

Prior to the model-building process, we conducted an in-depth examination of each variable we identified as valuable for explaining how districts differed with regard to this outcome variable. All of these predictors were district demographics/characteristics (e.g., SES, urbanicity, district achievement, etc.)

or district support variables (e.g., percentage of students receiving special education services, percentage of students with individualized education plans learning in LREs at least 80% of the school day, adoption of universal SEB standards or programs, etc.). For each of these explanatory variables, we conducted univariate descriptive analyses including examinations of the frequencies and percentages of districts within each subgroup for categorical predictors and means, standard deviations, percentiles, and so on, for continuous variables. In addition, bivariate analyses incorporated cross-tabulations and chi-squared tests of independence for categorical predictors, as well as overall mean and subgroup-mean comparisons for continuous predictors to examine the relationships between each independent variable and the current SEB approach outcome variable. Preliminary analyses also comprised logistic regression and multinomial logistic regression models to explore how the identified explanatory variables functioned, both individually and in combination, to explain the choice of district-level SEB approach.

After conducting these preliminary analyses, we built a series of multinomial logistic regression models to explain district-level choices regarding implemented SEB screening approaches. The initial theoretical model included seven independent variables: census region (South), urbanicity (urban), district-level socioeconomic status (SES; ses_c), percentage free lunch (flunchperc_10u_c), Grade 3 district achievement (DACH_3_c), elementary SEB programs (S23a_rSDN), and secondary SEB programs (S23f_rSDN). Model estimation revealed that census region, percentage free lunch, Grade 3 district achievement, and secondary SEB programs were not significant predictors of the district-level choice of SEB approach, after accounting for urbanicity, SES, and presence of elementary SEB programs in the district ($p > .05$; see Table 6). Therefore, we removed census region, percentage free lunch, and secondary SEB programs from this model. However, we retained the district-level achievement predictor as a control variable for subsequent models. This produced the trimmed theoretical model for which parameter estimates appear in Table 7 (see Figure 1 for a visual of the multinomial logistic regression [MNLR] models).

The last step in the MNLR modeling progression focused on potential moderation effects (i.e., Did any of the uncovered main effects change as a function of the level of another predictor in the model?). We tested one two-way interaction between urbanicity and SES and retained this significant effect for the final MNLR model. Table 8 presents the parameter estimates for this model, and Table 9 displays the marginal probabilities of selecting each screening approach for a variety of different district types. Overall, results from the final MNLR model echoed our descriptive findings such that districts tended to favor IRTI approaches, as evidenced by the model intercepts, which can be interpreted as ratios of the odds of a given pair of outcomes. For example, the intercept for the IRTI versus ERNO comparison demonstrated that the odds ratio for these techniques was more oriented toward IRTI methods, indicating that districts tended to favor the IRTI approaches over ERNO options

Table 6
Multinomial Logistic Regression Parameter Estimates: Initial Theoretical Model

					95% CI	
Parameter	Estimate	*SE*	*t*	*p*	*LL*	*UL*
IRTI vs. ERNO						
South	−0.39	0.24	−1.67	.095	−0.86	0.07
Urban	1.04	0.44	2.40	.017	0.19	1.90
SES	0.34	0.19	1.73	.083	−0.04	0.71
% Free lunch	−0.06	0.12	−0.52	.605	−0.29	0.17
District achievement	−0.26	0.17	−1.52	.129	−0.60	0.08
Elementary SEB programs	0.69	0.28	2.42	.016	0.13	1.25
Secondary SEB programs	0.10	0.29	0.35	.723	−0.47	0.67
Intercept	1.14	0.16	6.92	.001	0.82	1.46
FASA vs. ERNO						
South	−0.16	0.32	−0.49	.624	−0.79	0.48
Urban	1.08	0.52	2.09	.037	0.07	2.10
SES	0.54	0.25	2.15	.032	0.05	1.02
% Free lunch	0.10	0.15	0.65	.515	−0.20	0.40
District achievement	0.002	0.20	0.01	.994	−0.39	0.39
Elementary SEB programs	0.81	0.37	2.21	.027	0.09	1.53
Secondary SEB programs	0.07	0.36	0.18	.855	−0.64	0.77
Intercept	−0.46	0.23	−1.99	.047	−0.91	−0.01
FASA vs. IRTI						
South	0.24	0.27	0.87	.385	−0.30	0.77
Urban	0.04	0.36	0.11	.916	−0.66	0.74
SES	0.20	0.20	1.03	.305	−0.18	0.59
% Free lunch	0.16	0.11	1.45	.148	−0.06	0.38
District achievement	0.26	0.14	1.87	.062	−0.01	0.54
Elementary SEB programs	0.12	0.28	0.44	.662	−0.43	0.67
Secondary SEB programs	−0.04	0.25	−0.15	.882	−0.54	0.46
Intercept	−1.60	0.20	−8.03	<.001	−1.99	−1.21

Note. $F(14, 870) = 3.34$, $p < .001$. Parameter estimates presented in logits. CI = confidence interval; *UL* = upper limit; *LL* = lower limit; *SE* = standard error; SES = socioeconomic status; SEB = social, emotional, and behavioral; ERNO = External Referral or No Approach to SEB Screening; IRTI = Internal Referral or Teacher Intervention; FASA = Familiar Adult Nomination or Screening for All.

($\beta = 1.03$, $p < .001$, 95% confidence interval [CI: 0.77, 1.29]). When comparing FASA and IRTI, the model intercept also demonstrated favor for IRTI methods, suggesting that districts tended to implement IRTI techniques more often than FASA ($\beta = -1.52$, $p < .001$, 95% CI [−1.85, −1.20]). Finally, for the comparison of FASA and ERNO, the odds ratio was more oriented toward ERNO than FASA ($\beta = -0.49$, $p = .009$, 95% CI [−0.86, −0.12]; see Table 8), suggesting that districts were more likely to implement ERNO approaches over FASA techniques.

Table 7
Multinomial Logistic Regression Parameter Estimates: Trimmed Theoretical Model

					95% CI	
Parameter	Estimate	*SE*	*t*	*p*	*LL*	*UL*
IRTI vs. ERNO						
Urban	1.17	0.43	2.72	.007	0.33	2.02
SES	0.55	0.11	5.05	<.001	0.34	0.77
District achievement	−0.26	0.14	−1.86	.063	−0.54	0.01
Elementary SEB programs	0.81	0.19	4.36	<.001	0.45	1.18
Intercept	1.03	0.13	7.79	<.001	0.77	1.29
FASA vs. ERNO						
Urban	1.38	0.50	2.75	.006	0.39	2.36
SES	0.47	0.15	3.18	.002	0.18	0.77
District achievement	−0.07	0.17	−0.43	.664	−0.41	0.26
Elementary SEB programs	0.81	0.25	3.29	.001	0.33	1.30
Intercept	−0.51	0.19	−2.68	.007	−0.88	−0.14
FASA vs. IRTI						
Urban	0.20	0.33	0.63	.531	−0.44	0.84
SES	−0.08	0.13	−0.63	.532	−0.33	0.17
District achievement	0.19	0.13	1.50	.135	−0.06	0.44
Elementary SEB programs	0.00	0.20	−0.01	.994	−0.39	0.39
Intercept	−1.54	0.17	−9.32	<.001	−1.87	−1.22

Note. $F(8, 988) = 6.59$, $p < .001$. Parameter estimates presented in logits. CI = confidence interval; *UL* = upper limit; *LL* = lower limit; *SE* = standard error; SES = socioeconomic status; SEB = social, emotional, and behavioral; ERNO = External Referral or No Approach to SEB Screening. IRTI = Internal Referral or Teacher Intervention; FASA = Familiar Adult Nomination or Screening for All.

In other words, controlling for district urbanicity, SES, achievement, and adoption of elementary SEB programs, DAs reported implementing IRTI more often than ERNO or FASA and using ERNO more often than FASA.

Moreover, the marginal probabilities of employing each screening approach in average-achieving, average-SES, nonurban districts without elementary SEB programs reiterated these findings. In such districts, the overall probabilities of selecting IRTI, ERNO, and FASA techniques were .64, .23, and .14, respectively. These margins suggested that districts were more likely to implement IRTI over ERNO ($\Delta = .41$, $p < .001$) and FASA ($\Delta = .50$, $p < .001$).

Given that the model intercepts described above can be viewed as odds ratios for pairs of SEB screening approaches, it is also appropriate to think of the remaining MNLR model parameters (i.e., regression slopes) as changes to the logs of these odds ratios. In other words, each additional modeled predictor alters the degree to which a specified odds ratio is more oriented toward

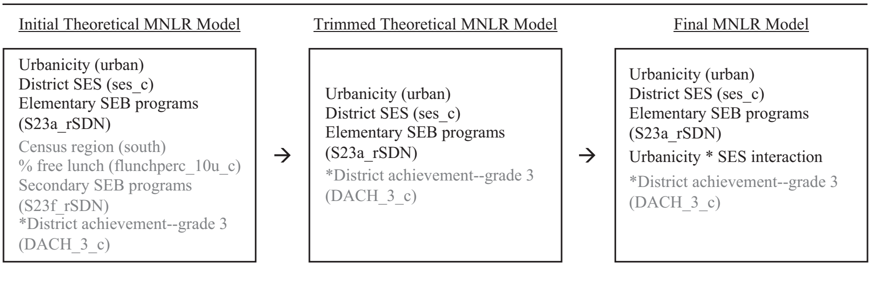

Figure 1. **Multinomial logistic regression (MNLR) model progression. This figure represents the three distinct steps in the MNLR modeling process. These included estimation of the initial theoretical model, the trimmed theoretical model, and the final model with interactions. Black type denotes significant predictors of current social, emotional, and behavioral (SEB) approach at each step in the modeling process. Grey type identifies nonsignificant predictors of current SEB approach.**

*Denotes nonsignificant predictors retained for further modeling, as control variables.

one approach over another. From this perspective, it was clear that the presence of elementary SEB programs in districts increased the orientation of the overall odds ratios more toward the IRTI and FASA techniques. In other words, districts with elementary SEB programs were significantly more likely than districts without such programs to favor the IRTI ($\beta = 0.81$, $p < .001$, 95% CI [0.45, 1.18]) or FASA ($\beta = 0.80$, $p = .001$, 95% CI [0.32, 1.28]) approaches, as compared to external methods. However, these districts were not more likely than districts without elementary SEB programs to use screening (FASA over IRTI: $\beta = -0.01$, $p = .947$, 95% CI [−0.41, 0.38]), after controlling for urbanicity, SES, and district-level achievement.

In addition, when solely focusing on nonurban districts of average SES and achievement, the probabilities of selecting ERNO, IRTI, and FASA approaches were .12, .73, and .16, respectively, for districts with elementary SEB programs and .23, .64, and .14, respectively, for districts without these programs. Hence, nonurban districts with elementary SEB programs were less likely to implement ERNO ($\Delta = .11$, $p = .009$) and more likely to implement IRTI ($\Delta = .09$, $p < .001$).

District urbanicity also affects the odds ratios comparing SEB approaches by increasing the orientation of these ratios toward FASA techniques. More specifically, urban districts were significantly more likely than nonurban districts to adopt FASA approaches, as compared to ERNO techniques ($\beta = 1.42$, $p = .042$, 95% CI [0.05, 2.79]), after controlling for SES, achievement, and the presence of elementary SEB programs.

Specifically considering districts of average SES and achievement without elementary SEB programs, the probabilities of selecting ERNO, IRTI, and

Table 8
Multinomial Logistic Regression Parameter Estimates: Final Model

					95% CI	
Parameter	Estimate	*SE*	*t*	*p*	*LL*	*UL*
IRTI vs. ERNO						
Urban	1.05	0.64	1.65	.100	−0.20	2.31
SES	0.58	0.11	5.10	<.001	0.35	0.80
District achievement	−0.27	0.14	−1.88	.061	−0.55	0.01
Elementary SEB programs	0.81	0.19	4.36	<.001	0.45	1.18
Urban * SES	−0.20	0.50	−0.39	.698	−1.18	0.79
Intercept	1.03	0.13	7.74	<.001	0.77	1.29
FASA vs. ERNO						
Urban	1.42	0.70	2.03	.042	0.05	2.79
SES	0.41	0.15	2.66	.008	0.11	0.70
District achievement	−0.07	0.17	−0.42	.678	−0.41	0.26
Elementary SEB programs	0.80	0.25	3.25	.001	0.32	1.28
Urban * SES	0.48	0.57	0.84	.400	−0.64	1.61
Intercept	−0.49	0.19	−2.60	.009	−0.86	−0.12
FASA vs. IRTI						
Urban	0.36	0.33	1.10	.269	−0.28	1.01
SES	−0.17	0.13	−1.27	.206	−0.43	0.09
District achievement	0.20	0.13	1.54	.125	−0.05	0.45
Elementary SEB programs	−0.01	0.20	−0.07	.947	−0.41	0.38
Urban * SES	0.68	0.28	2.41	.016	0.13	1.23
Intercept	−1.52	0.17	−9.22	<.001	−1.85	−1.20

Note. $F(10, 986) = 5.97$, $p < .001$. Parameter estimates presented in logits. To generate this model, we utilized factor variables in STATA (e.g., *i.urban*) for the two modeled categorical predictors. Factor variables produce a set of "virtual variables" (StataCorp, 2017, p. 101), one for each level of the specified observed variable. These virtual variables act as indicators, equaling "1" when the original observed variable takes on the level associated with that virtual variable and "0" otherwise. However, the first category of the observed variable does not receive a typical dichotomous indicator value for its virtual variable; instead, it equals "0" for every case. This ensures that the first category acts as the reference category or base value against which the remaining observed variable categories are compared during analysis. See the *Stata User's Guide* for more information. CI = confidence interval; *UL* = upper limit; *LL* = lower limit; *SE* = standard error; SES = socioeconomic status; SEB = social, emotional, and behavioral; ERNO = External Referral + No Approach to SEB Screening; IRTI = Internal Referral + Teacher Intervention; FASA = Familiar Adult Nomination + Screening for All.

FASA screening methods were .23, .64, and .14, respectively, for nonurban districts and .09, .70, and .22, respectively, for urban districts,. Comparisons of these probabilities within screening approach for urban and nonurban districts revealed that urban districts were significantly less likely to utilize ERNO approaches ($\Delta = .14, p < .001$) and significantly more likely to implement IRTI

Table 9
Multinomial Logistic Regression: Predicted Marginal Probabilities

Variable	Elementary Programs	Urbanicity	SES	District Achievement		ERNO MP	IRTI MP	FASA MP
Elementary Programs	0	0	0	0		0.23	0.64	0.14
	1	0	0	0		0.12	0.73	0.16
Urbanicity	0	0	0	0		0.23	0.64	0.14
	0	1	0	0	*ns*	0.09	0.70	0.22
	1	0	0	0		0.12	0.73	0.16
	1	1	0	0	*ns*	0.04	0.73	0.23
SES	0	0	−1.22	0		0.36	0.50	0.14
	0	0	0.06	0		0.22	0.64	0.14
	0	0	1.16	0		0.13	0.73	0.13
	1	0	−1.22	0		0.20	0.63	0.17
	1	0	0.06	0		0.11	0.73	0.16
	1	0	1.16	0		0.06	0.80	0.14
Urbanicity * SES	0	1	−1.22	0		0.14	0.73	0.12
	0	1	0.06	0	*ns*	0.08	0.69	0.22
	0	1	1.16	0	*ns*	0.05	0.61	0.34
	1	1	−1.22	0		0.07	0.80	0.13
	1	1	0.06	0	*ns*	0.04	0.73	0.23
	1	1	1.16	0	*ns*	0.02	0.63	0.35

Note. SES and District Achievement were continuous, mean-centered variables; therefore, SES values of zero represent schools of average SES, and District Achievement values of zero represent districts of average achievement. SES values of −1.22, 0.06, and 1.16 represent the 10th, 50th, and 90th percentile values for this variable. NS indicates that the identified individual ERNO PP (margin) was not statistically significantly different from zero ($p >$ .05). SES = socioeconomic status; ERNO = External Referral + No Approach to SEB Screening; IRTI = Internal Referral + Teacher Intervention; FASA = Familiar Adult Nomination + Screening for All; MP = Marginal Probability; *ns* = not significant.

(Δ = .06, p = .016). Notably, these marginal probability trends also held for districts with elementary SEB programs (see Table 9).

SES also significantly affected the odds ratios comparing SEB approach preferences, in favor of IRTI and FASA over ERNO methods. Specifically, higher-SES districts were significantly more likely than lower-SES districts to utilize IRTI (β = 0.58, $p < .001$, 95% CI [0.35, 0.80]) or FASA (β = 0.41, p = .008, 95% CI [0.11, 0.70]), as compared to ERNO screening techniques. In contrast, SES did not significantly impact the choice to implement FASA, in relation to IRTI (β = −0.17, p = .206, 95% CI [−0.43, 0.09]), after accounting for urbanicity, achievement, and elementary SEB programming.

Several important findings emerged concerning the impact of SES in non-urban, average-achieving districts without elementary SEB programs. First, as SES increased, the probability of using ERNO decreased from .36 to .22 when

SES changed from low[1] to moderate[2] (Δ = .14, p = .006) and from .22 to .13 when SES rose from moderate to high[3] (Δ = .09, p = .045). In contrast, as SES increased, the probability of implementing IRTI improved significantly, from .50 to .64 when SES shifted from low to moderate (Δ = .14, $p < .001$), and from .64 to .73 when SES grew from moderate to high (Δ = .09, $p < .001$). Interestingly, the probability of choosing FASA did not change significantly as a function of SES. As with urbanicity, these marginal probability trends were similar in districts with and without elementary SEB programs (see Table 9).

Furthermore, an investigation of the moderating effect of urbanicity on the impact of SES on current district-level SEB screening approach provided additional detail about the influence of SES. Examination of the MNLR model parameter estimates for the interaction between SES and urbanicity only revealed a significant moderation effect when comparing the FASA and IRTI approaches to SEB screening (β = 0.68, p = .016, 95% CI [0.13, 1.23]). In other words, urban districts with high SES tended to favor FASA approaches over IRTI methods. The marginal probabilities presented in Table 9 provided additional support for this finding. For example, after accounting for district achievement and elementary SEB programs, the probabilities of using FASA and IRTI approaches were .34 and .61 in high-SES, urban districts. In contrast, margins for these methods were .12 and .73, respectively, in urban districts with low SES levels. Therefore, increasing from low to high SES in urban districts corresponded with a significant increase in the probability of implementing FASA (Δ = .22, $p < .001$) and a significant decrease in the probability of using IRTI (Δ = .12, $p < .001$).

It is notable that the marginal probability trends associated with changes in district SES differed as a function of urbanicity. Specifically, in nonurban districts, the probabilities of implementing FASA and IRTI techniques were .13 and .73, respectively, when SES was high and .14 and .50, respectively, when SES was low, after controlling for district achievement and elementary SEB programs. Consequently, increasing from low to high SES in nonurban districts coincided with a significant increase in the probability of using IRTI methods. Taken together, this significant interaction between urbanicity and SES suggested that in nonurban districts, increased SES did not affect the probability of implementing FASA but did significantly increase the probability of using IRTI techniques. Conversely, in urban districts, increased SES related to a significant decrease in the probability of using IRTI and a significant increase in the probability of using FASA. Hence, the influence of SES on the odds ratio comparing the IRTI and FASA methods varied as a function of the urbanicity of the district.

Research Question 3: Differences in Districts Using More or Less Proactive SEB Approaches

A propensity score analysis was conducted to determine whether there were differences between those districts reporting FASA versus ERNO with regard to behavioral outcomes or usability, after equating the two groups based on their propensity to use either FASA or ERNO as the primary current SEB approach. Our behavioral outcome measures were percentage of (a) special education students in LRE at least 80% of the day, (b) students identified as ED, (c) students receiving 504 plans, (d) out-of-school suspensions, (e) in-school suspensions, (f) dropouts, (g) chronic absenteeism, and (h) harassment and bullying. Our usability measures were the Knowledge, Willingness to Change, and Feasibility subscales of the URP-NEEDS. Our propensity score analysis balanced the two groups representing the most proactive (FASA) and the least proactive SEB approach (ERNO) on a large set of pretreatment covariates (descriptions of these variables can be found in Table 10). First, we fit a logistic regression model to predict membership in one of two groups included in these analyses (FASA or ERNO) and computed the propensity scores, which represented the probability of being in the FASA group, given the district's scores on the 13 covariates. All of the continuous covariates were grand mean centered for the logistic regression analysis. In addition, district survey weights were applied.

Because we had equal numbers of districts in each of the two groups, we used inverse probability of treatment weights (IPTW) to balance the two groups. IPTW weights each participant by their conditional probability of treatment (Guo & Fraser, 2009). Propensity score weighting techniques have one major advantage as compared to matching or stratification techniques. In general, they utilize all cases in the sample, albeit weighted differentially according to their probability of treatment receipt. However, a related disadvantage is that there is a possibility that certain cases may have extremely high weights (if the probability of group membership is extremely low), in which case it is necessary to either remove those (not typically recommended) or use stabilization techniques (Robins, 2000) that decrease the variance of the IPTW (Guo & Fraser, 2009). Therefore, prior to conducting the average treatment effect analyses with the propensity score weights, we examined the magnitude of the IPTWs, as is recommended. None of our IPTWs were larger than 2.84, which is not considered extreme in this context. Given the lack of extreme weights, we conducted the IPTW analysis with all cases included, and we did not use stabilization techniques. As shown in Table 10, schools that engaged in more proactive SEB approaches were more likely to have higher achievement and higher SES. After applying the IPTW, none of the standardized mean differences on the covariates exceeded $|.035|$, which indicates that balance was achieved.

Results from the propensity score weighted analysis are in Tables 11 (usability) and 12 (behavioral outcomes). For these distal behavioral outcomes, none of the differences between the two groups were statistically significantly different from 0. Results indicated that districts using FASA as a current approach scored approximately .48 points higher on the *Knowledge* subscale of the URP-NEEDS. The pooled standard deviation for the *Knowledge* subscale

Table 10

Unadjusted and Adjusted Cohen's *d* Effect Sizes to Assess the Degree of Balance in the Sample Before and After Weighting

Covariates	Unadjusted	Adjusted *d*
Percent Hispanic	−0.033	−0.019
Percent Black	−0.030	−0.001
Percent White	0.098	0.030
Gini	−0.101	−0.012
Percent ELL	−0.083	−0.021
Urban	0.166	−0.041
Student-teacher ratio	−0.022	−0.028
BA+	0.423	−0.021
Percent charter	−0.049	−0.035
Percent unemployed	−0.154	0.006
Per-pupil expenditure	0.078	0.007
District achievement	0.127	−0.025
Poverty	−0.329	0.004

Note. ELL = English language learner.

was 0.86; this difference represents a Cohen's *d* effect size of 0.56, and was statistically significant ($p < .001$). In addition, districts using FASA as a current SEB approach scored approximately 0.23 points higher on the *Willingness to Change* subscale of the URP-NEEDS. The pooled standard deviation for the *Willingness to Change* subscale was 0.82; this difference represents a Cohen's *d* effect size of 0.28, and was statistically significant ($p = .02$). Districts using FASA as the current approach also scored approximately 0.24 points higher on the *Feasibility* subscale of the URP-NEEDS. However, the pooled standard deviation for the *Feasibility* subscale was 1.03; representing a Cohen's *d* effect size of 0.23, which was not statistically significant ($p = .06$).

Discussion

The purpose of this study was to explore approaches to identifying and supporting student SEB needs in a nationally representative sample of U.S. public school districts. Overall, results did not support a consistent picture related to choice of SEB approach, but did find that the most popular approach involves referral of students exhibiting SEB concerns to an internal support team. In addition to enhancing understanding about the use of SEB approaches in school districts across the nation, findings also provided a novel picture of differences in SEB approaches and influences on outcomes.

Table 11
Regression Results for the Usability Rating Profile–NEEDS, Using Inverse Probability of Treatment Weights

Effects	Coefficient	*SE*	*t*	*p*	Lower Limit	Upper Limit
Knowledge intercept	3.57	0.08	42.83	.00	3.41	3.74
Knowledge slope	0.48	0.11	4.50	.00	0.27	0.70
Willingness intercept	3.92	0.07	52.45	.00	3.78	4.07
Willingness slope	0.23	0.10	2.26	.02	0.03	0.43
Feasibility intercept	3.59	0.09	39.04	.00	3.41	3.77
Feasibility slope	0.24	0.13	1.89	.06	−0.01	0.49

Research Question 1: Current Approaches to Identifying and Supporting Student SEB Concerns

The descriptive analysis related to the national landscape of SEB approaches in schools yielded several interesting findings. Whereas almost all U.S. public school districts reported having academic standards, less than half had SEB standards. Although DAs reported that state mandates typically drove academic standards, decisions about SEB standards and programs generally occurred at the district or building levels. For example, more than 8 in 10 districts reported having state-mandated academic standards, whereas slightly more than 2 in 10 reported their academic standards are district decisions and less than 1 in 10 indicated building-level decisions. In contrast, for districts who do have SEB standards, the picture of the primary influencers differs from that of academic standards, with district-wide decisions having the biggest influence, followed by building level decisions, and state mandates playing a very small role. That is, only about 20% of those surveyed indicated their SEB standards are state mandated (21% at the elementary level and 18% at the secondary level). Nearly half of DAs surveyed indicated that SEB standards are a district decision, whereas approximately one third (32% and 37%, respectively) said they are established at the building level. These findings are unsurprising given the landscape at the national level. That is, whereas the Every Student Succeeds Act (2015) requires that all states have challenging academic standards across reading, math, and science, comparable expectations have not been set within the SEB domain. In fact, a recent review found that only 11 states had social-emotional learning standards for Grades K–12 (Eklund et al., 2019), which is consistent with the 18% to 21% of respondents reporting state mandates within the current study.

In addition, 57% of respondents reported use of universal SEB programs at the elementary level, whereas only 40% reported use at the secondary level. The greater emphasis on use of universal SEB programs in elementary schools might not be unexpected given the developmental expectation that younger

Table 12

Regression Results for Distal Behavioral Outcomes, Using Inverse Probability of Treatment Weights

Effects	Coefficient	*SE*	*t*	*p*	Lower Limit	Upper Limit
Least restrictive environment 80% intercept	65.70	1.35	48.75	.00	63.05	68.36
Least restrictive environment 80% slope	1.80	1.83	0.98	.33	−1.8	5.41
Percent identified as EBD intercept	1.11	0.11	10.03	.00	0.89	1.33
Percent Identified as EBD slope	0.44	0.34	1.31	.19	−0.22	1.10
Percent 504 intercept	0.47	0.06	7.47	.00	0.35	0.60
Percent 504 slope	0.03	0.08	0.32	.75	−0.13	0.18
Percent OS suspension	0.80	0.07	10.86	.00	0.65	0.94
Percent OS suspension	0.10	0.11	0.84	.40	−0.13	0.32
Percent IS suspension	1.58	0.22	7.19	.00	1.15	2.01
Percent IS suspension	0.10	0.30	0.34	.74	−0.49	0.69
Percent dropout intercept	7.13	0.86	8.27	.00	5.38	8.89
Percent dropout slope	2.22	3.68	0.60	.55	−5.26	9.69
Percent chronic absenteeism intercept	3.38	0.48	7.12	.00	2.45	4.32
Percent chronic absenteeism slope	0.03	0.63	0.05	.96	−1.21	1.28
Percent harassment/bullying intercept	0.11	0.03	4.20	.00	0.00	0.16
Percent harassment/bullying slope	0.03	0.05	0.52	.60	0.00	0.12

Note. EBD = emotional disability/emotional behavioral disorder; OS = out-of-school suspension; IS = in-school suspension.

children need to learn and adapt to school rules and expectations, which includes prosocial behavior and self-regulation skills (e.g., Welsh et al., 2016). Similarly, less than 10% of respondents indicated that there was a state mandate to implement universal SEB programs. The majority of respondents indicated that this choice was either a district (roughly 60%) or building (roughly 32%) decision. Findings related to the small role of state mandate in decisions around SEB standards and programs appear consistent with guidance around SEB screening practices. For example, in their recent review of state departments of education websites, Briesch et al. (2019) found limited specificity in recommendations or mandates around universal SEB screening. Rather, the majority of available guidance was informational, often emphasizing general tiered systems of service delivery without specificity around SEB assessment.

With regard to the current primary approach to SEB identification and support, within-building approaches tended to be the most commonly used, with two of the three top-identified approaches involving internal identification and management. In fact, the majority of districts in this sample reported that their primary SEB screening approach involved referring students to an internal support team (i.e., *Internal Referral*; 54.70%), followed by referring students to an outside consultant or agency (i.e., *External Referral*; 12.11%), and encouraging teachers to address SEB problems independently in their classrooms (i.e., *Teacher Intervention*; 10.14%). Conversely, approaches that incorporate standard screening procedures applied to all students in a given population (i.e., *Screening for All*; 5.54%) or those students nominated by their teachers (i.e., *Familiar Adult Nomination*; 9.81%) were less highly endorsed. Overall, current findings appear consistent with prior studies with convenience samples in supporting SEB screening in schools is not yet widespread (Bruhn et al., 2014; Romer & McIntosh, 2005). Although uptake in universal SEB screening practices in schools does not appear to have been realized to date, the current findings do suggest that districts generally perceive responsibility for managing student SEB needs internally as opposed to historical perspectives that prioritize academic needs and abdicate SEB responsibility externally. In addition, DAs were asked their perceptions of the usability of the current approach. Generally, patterns in responses are what might be expected; for example, those districts with a primary SEB approach involving *External Referral* also indicated the highest need for supports from external consultants and positive relationships with community agencies. Interestingly, those districts whose reported SEB approach was *Screening for All* also indicated the highest usability on factors of understanding and feasibility.

Research Question 2: Patterns in Use of SEB Approaches

The second research question investigated patterns in use of SEB approaches as predicted by student demographics, district characteristics, and/or use of SEB standards and programs. Significant predictors that included variables from each of the individual models were identified and used in building the final model. Results supported that the use of an SEB approach proactive in using standard procedures applied to all (FASA) was not overwhelmingly predicted by any combination of the included variables. This may be partially attributed to the low endorsement of this option as the primary current SEB approach (roughly 15%). However, some interesting results were revealed through the final model. First, those districts with elementary SEB programs had increased odds of using internally managed SEB approaches (i.e., FASA, IRTI) over externally managed approaches (ERNO). Second, urban districts were significantly more likely than nonurban districts to use FASA versus ERNO, after controlling for SES, achievement, and presence of elementary SEB programs. Third, higher SES districts were more likely than lower SES districts to utilize internally managed (FASA, IRTI) over externally managed (ERNO) approaches. Urban districts high in SES tended to favor FASA approaches over IRTI methods. Results supported a significant interaction between urbanicity and SES given that the influence of SES on the odds ratio comparing the IRTI and FASA methods varied as a function of the district urbanicity. In nonurban districts, increased SES did not affect the probability of implementing FASA but did significantly increase the probability of using IRTI techniques. Conversely, in urban districts, increased SES related to a significant decrease in the probability of using IRTI and a significant increase in the probability of using FASA.

Research Question 3: Differences in Districts Using More or Less Proactive SEB Approaches

The final research question explored potential differences in behavioral outcomes between groups whose current primary SEB approach was most versus least proactive. Results of the propensity score weighted analysis indicated that districts that use more proactive approaches that include standard procedures applied to all students in a population scored higher on the usability factors of knowledge and willingness to change. However, there were no differences between the groups with regard to more distal outcomes (e.g., percentage of students identified for special education, percentage of students identified with emotional behavioral disturbance, percentage of students with 504 plans, percentage of in-school and out-of-school suspensions, and percentage of chronic absences). Therefore, we did not find evidence that use of a more proactive SEB approach predicts district-level behavioral outcomes. Many potential reasons exist for this null finding, perhaps most substantially related to the outcome measures available for use in this study. For example, it might not be reasonable to expect that the percentage of students identified for any form of special education services would decrease if a district engages in a proactive SEB approach. Although a more proactive SEB approach might decrease the percentage of students identified as ED, these shifts are likely to occur incrementally over longer periods of time. Thus, changes in SEB approaches implemented in early grades cannot be expected to change district-level percentages of suspensions or absences the following year. Systems change literature would suggest a more realistic lag occurs over many years.

Limitations and Directions for Future Research

Despite employing rigorous survey methodology to obtain a nationally representative sample, this study is not without limitations. First, standardized surveys force a researcher to simplify complex constructs in order to produce a measure that is clear, comprehensible, and broadly applicable. In creating measures around SEB approaches we may have failed to capture the complexity of district approaches. Future research may wish to consider mixed methods projects that add the use of qualitative methodologies in order to better understand the unique ways in which schools carry out the broad SEB approaches identified in this study, probe the perceptions of usability, and the adoption and sustainment of a particular approach.

Second, although cross-sectional studies can provide an intricate "snapshot" of the issue and population, such studies are limited by the fact that they are carried out at one time point. Because they lack temporal variation, single surveys cannot provide strong evidence of causation. Related are the challenges in obtaining appropriate comparison data. We had anticipated updated databases would be released within a time frame that corresponded with the survey field period, but this was not the case. Thus, for some data, there is a lag between when variables were measured (i.e., 2013–2014 reporting for most of publicly available databases) and the 2015–2016 survey data collection. In addition, special education data were not included in national databases, requiring that we request and gather information at the individual state or district level, and then transform it within our larger database. It is important to note that it may be difficult to detect improvements in many of the outcomes of interest given some outcomes reported were already quite small (e.g., disciplinary data). Our exploration was limited with regard to capacity to isolate the outcomes most directly related to SEB identification and support. Given the low percentages of U.S. school districts currently implementing SEB screening; however, this presents an opportunity for future researchers to examine the potential and more direct linkages between the use of SEB approaches and student outcomes experimentally.

Finally, the current study explored district-level reports of approaches, and thus, we acknowledge that there may be variation within a district in regard to individual schools. For example, universal screening may be expected to have a broader impact on student outcomes in the elementary grades given screening for general risk is more likely and less intensive intervention efforts may prove effective. Variability may also exist in the degree to which a district-wide SEB approach is implemented within a given building. Exploring both the approach taken and the linkages within student outcomes at the building level offer an important next step.

Summary and Implications

This study provides a critical glimpse into the current national landscape of district approaches to identifying and supporting the SEB needs of students. Overall, results support that recommended approaches that are proactive in early identification and support of student SEB needs are not widely used in U.S. public school districts. Findings regarding low rates of SEB screening practices may not be surprising given that supporting structures such as state guidance, district standards, and universal programs also appeared to occur at low rates. Although results related to the generally high endorsement for current SEB approaches that include internally managed options are encouraging, they do suggest work is needed to strengthen district capacity to engage in prevention-based frameworks for early identification of SEB needs. Particularly for those districts choosing an SEB approach that is externally managed or no approach, it is important for researchers to investigate, and leaders to recognize, the potential levers for supporting change, such as usability indicators (knowledge, feasibility, and willingness to change). Future research also needs to explore the inner and outer contexts in order to establish those conditions necessary for school personnel knowledge, skills, and attitudes for effective use of proactive SEB approaches to identifying and supporting student needs.

Appendix

Description of Variables Used for Multinomial Logistic Regression and Propensity Score Analyses

Variable	Description	MNLR	PS
Special Education (T1213Disab_PERC)	Percentage of district students receiving special education services in 2012–2013; created from project-collected district special education data and CCD data	×	
Least-Restrictive Environment (lre80_10u)	Percentage of district students who learned in least-restrictive environments at least 80% or more of the day in 2012–2013; from project-collected district special education data	×	
Elementary SEB Programs (S23a_rSDN)	1 if the district had adopted SEB programs at the elementary level, 0 otherwise; from DA Survey	×	
Secondary SEB Programs (S23f_rSDN)	1 if the district had adopted SEB programs at the secondary level, 0 otherwise; from DA Survey	×	
Understanding (KNOW_SDN)	Composite variable—Mean of URP items in knowledge factor (α = .94; 10 items); from DA Survey	×	
Willingness to Change (WILL_SDN)	Composite variable—Mean of URP items in willingness factor (α = .85; 4 items); from DA Survey	×	
Feasibility (FEAS_SDN)	Composite variable—Mean of URP items in Feasibility factor (α = .86; 4 items); from DA Survey	×	
Family-School Collaboration (FSC_SDN)	Composite variable—Mean of URP items in Family/School Collaboration factor (α = .77; 3 items); from DA Survey	×	
External Supports (EXSUP_SDN)	Composite variable—Mean of URP items related to the necessity of external supports for district's current SEB approach (α = .73; 3 items); from DA Survey	×	
Census Region (south)	1 if the district was located in the South census region, 0 otherwise; created from ANSI state code (FIPST)	×	
Socioeconomic Status (ses)	District socioeconomic status; from SEDA	×	
Urbanicity (urban)	1 if the district was urban, 0 otherwise; from SEDA	×	×
Per-Pupil Expenditures (ppexp)	District's average per-pupil expenditures; from SEDA	×	×
Student-Teacher Ratio (stutch)	Average student-teacher ratio; from SEDA	×	×

(continued)

Appendix **(continued)**

Variable	Description	MNLR	PS
District Achievement (DACH_3)	Composite variable: Mean of third-grade district math achievement and third-grade district reading achievement; created from SEDA data	×	×
Percent Hispanic (perhsp)	Percentage of Hispanic students in the district; from SEDA	×	×
Percent Black (perblk)	Percentage of Black students in the district; from SEDA	×	×
Percent ELL (perell)	Percentage of ELL students in the district; from SEDA	×	×
Percent White (perwht)	Percentage of White students in the district; from SEDA		×
Gini (gini)	Gini index of income segregation; indicates the dispersion of income; Gini of 0 indicates equality of income distribution; a Gini near 1 indicates highly inequitable distribution of income; from SEDA		×
Percent College (baplus)	District percentage with at least a BA; from SEDA		×
Percent Charter (percharter)	Percentage of students in the district who attend charter schools; from SEDA		×
Percent Unemployed (unemp)	District percentage unemployed; from SEDA		×
District Poverty (childpov)	Percentage of children ages 5–17 in the district who live in poverty; from SEDA		×

Note. MNLR = multinomial logistic regression modeling/analyses; PS = propensity score analyses; CCD = National Center for Education Statistics Common Core of Data, Local Education Agency Universe Survey, 2013–2014; DA Survey = District Administrator Survey administered during the NEEDs^2 project; ANSI = American National Standards Institute; SEDA = Stanford Education Data Archive from the Center for Educational Policy Analysis (CEPA); SEB = social, emotional, and behavioral; URP = Usability Rating Profile; ELL = English language learner.

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Notes

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[1]Low SES = 10th percentile in district SES.

[2]Moderate SES = 50th percentile in district SES.

[3]High SES = 90th percentile in district SES.

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