

# Self-Report and Administrative Data on Disability and IEP Status: Examining Differences and Impacts on Intervention Outcomes

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## Abstract

Differences in perceptions of disability between students and administrators can play a role in youth's educational experience. This study used data from a cluster randomized controlled trial (C-RCT) of the Self-Determined Learning Model of Instruction (SDLMI) to first compare student self-report of disability status to matched administrative data and second to examine the impact of the data source utilized on trial outcomes. The findings demonstrate substantive gaps between self-reports and administrative reports of disability. While some differences might be expected, the size of the differences is notable, especially given that many students identified as having an Individualized Education Program in administrative data did not self-identify as receiving services or having a disability. The findings advance understanding of discrepancies in self-reported disability and administrative data in secondary intervention research. We also found the interpretation of group differences (students with vs. without disabilities) on trial outcomes was sensitive to the source of the data (self vs. administrative) used to establish disability status. This finding can inform future research and policy, as the data source selected to define disability populations across research studies likely has substantive impacts on conclusions drawn about the impact of interventions on students with disabilities. We cannot identify all the factors driving these differences. Nonetheless, the findings underscore the importance of providing clarity about decisions made in defining disability populations in intervention research.

## Keywords

self-determination, Self-Determined Learning Model of Instruction, disability status, self-report, administrative data

Discrepancies in disability identification have long been found in national surveys when comparing student, family, teacher, and school administrative data. For example, Rossi et al. (1997), using data from the 1988 National Educational Longitudinal Study (NELS:88), concluded disability classifications derived from each source led to “separate and distinct populations of students and that comparisons among these populations should be made with care” (p. 14). A more recent analysis of 2002 Educational Longitudinal Study (ELS:2002) data revealed that different educators teaching different subjects to the same student often disagreed in their identification of student disability (Cooc, 2018). Wagner et al. (2007), using data from the National Longitudinal Transition Study-2 (NLTS-2), found only 32% of students identified by district administrative data as receiving special education services identified themselves as having “any kind of disability or special need” (p. 15). In part, because of such findings, researchers and practitioners

frequently identify the importance of disability awareness instruction focused on enabling secondary students to identify their disability status and their support needs, in preparation for the transition from entitlement-based special education services to eligibility-driven programs after K–12 education, including postsecondary education and work-force accommodations (Flexer et al., 2013).

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However, disability identification is complex; both self- and administrative identification is influenced by multiple factors. In special education, for example, a disability diagnosis alone is not enough to qualify for special education services, evaluation data must also indicate the student needs special education supports and services because of the identified disability. Disability prevalence estimates vary based on the data source utilized and if the variable of interest is a diagnosed disability versus qualifying for an Individualized Education Program (IEP; Wittenburg & Loprest, 2007). Furthermore, there is no one universally accepted definition of disability or framework for classifying disability, particularly when transition-age students with disabilities are interacting across multiple systems (e.g., health, education, and vocational rehabilitation; Shogren & Wittenburg, 2020). Across administrative data systems, young people are frequently identified as having a disability based on different criteria (Honeycutt et al., 2014). Different stakeholders (e.g., students, families, and teachers) may define disability and its impacts on functioning in different ways, leading to differences in reporting (Lalvani, 2015).

Despite evidence of differences in perceptions of disability status, limited information exists on the size of the gap across self-report and administrative data. Inconsistencies in disability identification are recognized and calls have been issued for greater focus on consistent identification variables in large-scale descriptive research (Honeycutt et al., 2014). However, the implications of the decisions made in defining disability populations in intervention research have not been widely considered. This gap in knowledge is troublesome as we hypothesize decisions made about how to define disability populations could impact conclusions drawn about trial outcomes or “for whom” interventions are effective (Cook & Odom, 2013). Without clarity on how the populations that are included in intervention efficacy research are defined, it will be challenging for other researchers as well as policymakers and practitioners to make decisions about the adoption of effective interventions for specific student populations.

One strength of administrative data is that it provides an objective way to identify who participates in programs. For example, special education administrative data provides direct counts of youth who receive special education services and supports. However, there are two limitations of these administrative counts. First, this approach does not recognize the potential impact of self-perceptions on intervention outcomes. For example, youth self-perceptions of their disability status and support needs may also provide important and distinct information that could influence intervention outcomes, particularly in secondary classrooms. Second, services vary substantially across geographic areas. For example, youth who qualify for special education services in one school district might not

necessarily qualify for supports in other districts. Only considering administrative data fails to represent a youth’s self-perception of disability and their experiences in their environment. For example, disability researchers have found including self-reported perceptions of disability-related work limitations alongside administrative disability information allows for better prediction of the receipt of Social Security Disability income benefits (Burkhauser et al., 2012).

A frequent challenge in special education research is that researchers often rely on only one source of data. There often is not an opportunity to regularly study or report convergence—or divergence—between self-report and administrative data on disability. To examine the potential consequences of not explicating these decisions, in the present study, we analyzed outcome data from the first year of a cluster randomized controlled trial (C-RCT) examining varying intensities of support for teachers implementing the *Self-Determined Learning Model of Instruction* (SDLMI; Shogren, Raley et al., 2018). Our goal was to examine the congruence between self-report and administrative disability data as well as the impact of the data source utilized. The overall focus of the three-year C-RCT was examining the impact online only vs. online + coaching supports for teacher implementation of the SDLMI as a universal or Tier 1 intervention in inclusive, general education core content classrooms with students with and without disabilities. In the present analysis, we were specifically interested in (a) agreement of self-reported and administrative data on disability in the sample from the C-RCT and (b) impacts of the disability data source utilized in analyses of the between groups effects on self-determination outcome data. Our research questions emerged as we were cleaning and validating data and engaging in preliminary analyses. Descriptive discrepancies were noticed between administrative and self-reported disability status. Given these discrepancies, our knowledge of research suggesting differences between self-report and administrative data on disability status, and the lack of clear guidance from the field on the impact of the differing disability data sources, we explored the following questions:

1. **Research Question 1:** Within self-report and administrative data, what is the level of agreement on disability status (yes/no) and IEP status (yes/no)?
2. **Research Question 2:** Across self-report and administrative data, what is the level of agreement on IEP status?
3. **Research Question 3:** Across self-report and administrative data, what is the level of agreement on disability status (yes/no) and disability label (autism, emotional disturbance, hearing impairment, intellectual disability, learning disability, multiple disabilities other health impairment, orthopedic

impairment, speech or language impairment, traumatic brain injury, or visual impairment)?

4. **Research Question 4:** Assuming differences, what is the impact of utilizing different data sources on self-determination outcomes, measured by the *Self-Determination Inventory: Student Report* (SDI:SR), during the first year of the C-RCT?

## Method

Data were from the first year (2018–2019) of an ongoing, 3-year C-RCT. During the first year, six high schools in two states in the Mid-Atlantic area participated.

### Participants in the C-RCT

In the first year, 1,002 ninth-grade students contributed data. The sample for the present analysis was narrowed to the 990 students for which we had self-determination outcome data, the dependent variable for Research Question 4. Table 1 provides student demographic information (e.g., grade level and race/ethnicity) obtained from administrative records for the sample of 990 students. Most participants were enrolled in ninth grade ( $n = 950$ , 96.0%) as this grade level was the focus of the first year of the C-RCT. A few students were in upper grades ( $n = 26$ , 2.6%) and in ninth-grade ELA or science class.

Consistent with implementation protocols in the C-RCT, all participating students received the SDLMI intervention in their targeted general education ELA or science class. Instruction was delivered in two 15-min mini-lesson sessions per week, with protocols for infusing content learned through the SDLMI (e.g., implementation of action plans to achieve goals) throughout the rest of the class period. For further details specific to the implementation of the SDLMI in inclusive, general education classrooms see Raley et al. (2018). Participating teachers who delivered SDLMI instruction included 12 (70.6%) general and 5 (29.4%) special education teachers. General and special educators were trained as a team in a standardized training in the summer 2018 (Bojanek et al., in press). Across participating schools, there were varying levels of collaboration between general and special education teachers in implementing the SDLMI, ranging from co-teaching to consultative models.

### Data Sources

**Administrative disability and IEP data.** Participating students were enrolled in schools in two states. In one state with three participating high schools, the state Department of Education (DOE) shared administrative data through a data-sharing agreement. In the second state with the remaining three schools, administrative data were collected through data-sharing agreements with two individual school

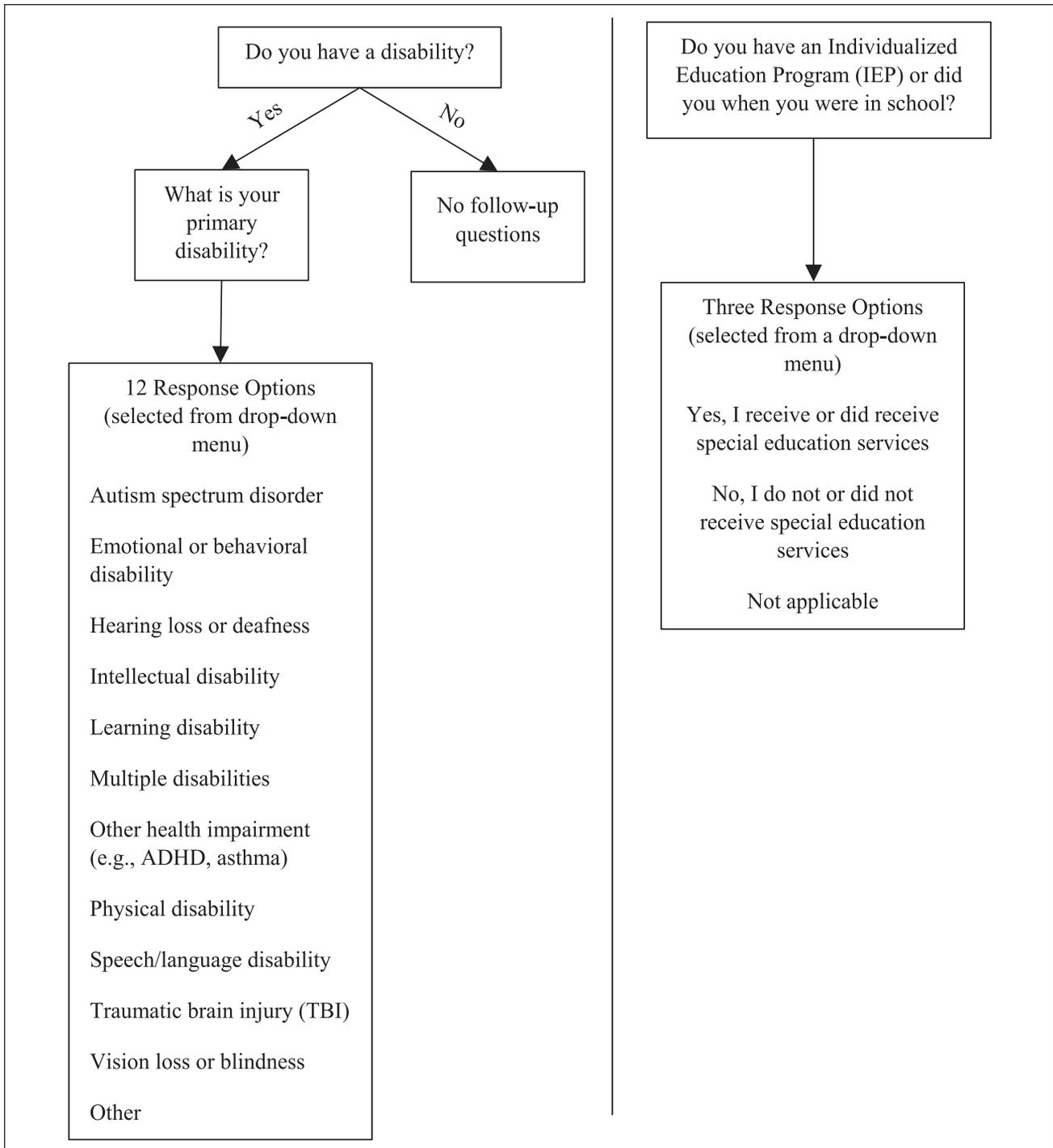
**Table 1.** Sample Demographics.

Characteristic	N = 990	
	n	%
<b>Gender</b>		
Female	458	46.3
Male	527	53.2
Missing	5	0.5
<b>Race/Ethnicity</b>		
Black/African American	395	39.9
American Indian/Alaska Native	5	0.5
Asian American	30	3.0
Hawaiian Native or Pacific Islander	3	0.3
Hispanic/Latinx	92	9.3
Two or more races	31	3.1
White/European American	426	43.0
Missing	8	0.8
<b>Grade</b>		
9 <sup>th</sup>	950	96.0
10 <sup>th</sup>	22	2.2
11 <sup>th</sup>	3	0.3
12 <sup>th</sup>	1	0.1
Missing	14	1.4
<b>English learner (EL) status</b>		
No	947	95.7
Yes	30	3.0
Missing	13	1.3
<b>Free and reduced-price lunch status</b>		
No	492	49.7
Yes	449	45.4
Missing	49	4.9

Note. Data are from administrative sources except for 34 cases for gender, grade, and EL, and 31 cases for race/ethnicity, which came from self-report. EL = English learner.

districts, with one district contributing data for two schools and a second district for the final school. While data files were received separately, data fields were the same across the districts in the state. Administrative data had separate variables for student IEP status (yes/no) and disability label; however, disability labels varied slightly across the two states and were recoded to be consistent with the Individuals with Disabilities Education Act (IDEA) classifications. We also created an overall disability label variable (yes/no) based on whether a disability label was indicated (referred to as disability status, consistent with the student self-report data).

**Self-reported disability and IEP data.** Self-report data came from a standardized demographic questionnaire appended to the end of the primary outcome measure, the *Self-Determination Inventory: Student Report* (SDI: SR; (SDI: SR: Shogren et al., 2020). The SDI: SR and demographic items were delivered via an online platform with built-in accessibility



**Figure 1.** Disability and IEP survey questions and answer options.  
 Note. IEP = Individualized Education Program.

features (e.g., items can be read aloud, definitions are available for difficult words or concepts like IEP). The demographic form contained 12 to 16 items (depending on branching logic) and asked for information such as age, gender, and race/ethnicity. Crucial to this study were two questions: “Do you have a disability?” and “Do you have an

Individualized Education Program (IEP) or did you when you were in school?” Figure 1 presents the possible response options to these questions.

Students completed the SDI:SR and demographic form at 3 time points: beginning, middle, and end of the academic year. Thus, it was possible students’ responses could change

across timepoints (e.g., reported no disability at the beginning of the year and then reported having a disability in the middle of the year). A large majority of students were consistent in how they responded across the 3 time points, with 93.5% of students having consistent responses for the disability and 94.6% of students having consistent responses for the IEP status variables. Although future research can explore factors that lead to change in responses to these items over the academic year (e.g., change in special education services, growing disability awareness, inconsistent engagement in the assessment system), in the present analyses, we collapsed responses over time, given the high degree of agreement. To deal with that fraction of cases in which students provided inconsistent responses for the same variable over time when collapsing, we took the conservative step of recording the variable as unknown or missing in the analyses ( $n = 64$ ; 6.5% for disability and  $n = 53$ ; 5.4% for IEP).

**Self-Determination Inventory: Student Report (SDI: SR).** The SDI: SR is a 21-item self-report measure of self-determination, designed to align with Causal Agency Theory (Shogren et al., 2015). Shogren et al. (2020) validated the SDI:SR for use with students ages 13 to 22, with and without disabilities. Shogren, Shaw, et al. (2018) provided data on differences in scores based on disability status and label and race/ethnicity, suggesting the tool is sensitive to differences across subpopulations. The assessment is delivered in a customized online platform, with built-in accessibility features (e.g., audio playback and in-text definitions) to ensure students with a wide range of needs can meaningfully engage with the measure as well as the demographic items that follow it (described previously). Each item on the SDI: SR is rated on a slider scale scored using the customized computer system, with discrete scores for each response, ranging from 0 (*Disagree*) to 99 (*Agree*). Consistent with classical test theory and previous inquiry, mean scores (across the 21 items) of the SDI:SR were derived.

### Data Analysis

We used a combination of descriptive, statistical, and graphical analyses to address Research Questions 1 to 3. We first explored agreement *within* each data source (IEP status and disability status; RQ1) as well as *across* data sources (self-report and administrative; RQ 2 and 3) to determine which, if any, were distinct constructs. There were two unique variables *within* each data source: indication of IEP status (yes/no for the receipt of special education services) and an indication of disability status (yes/no for the presence or absence of a disability and/or a specific disability label). Descriptively, we calculated absolute agreement (i.e., the number of agreements over the total number of comparisons) between the two sources being compared.

Statistically, we performed a series of McNemar (1947) tests to determine the significance of the directionality of disagreements (i.e., the frequency with which a given endorsed category was significantly more or less than another). We also used the odds ratio to gauge the strength of such associations and interpreted odds ratios as  $<1.22$  small,  $<1.86$  medium, and  $>3.0$  large (Mangiafico, 2016). We conducted analyses of missing data to determine if missing data on student self-report was missing completely at random (MCAR) with respect to administrative variables of interest using chi-square tests (Enders, 2010). The goal was to ensure there was no detectable bias between self-report and administrative sources (e.g., students were not systematically more likely to change responses, skip questions about disability, or select not applicable). Finally, we graphically depicted key findings to aid in interpretation.

To answer RQ 4, we analyzed SDI: SR data across the 3 time points (baseline, mid-year, and end of year), exploring the impact of disability on trial outcomes. We used sensitivity analysis (Thabane et al., 2013) to determine whether the use of self-report versus administrative data sources led to discrepancies in conclusions. We investigated whether the estimate of the differential impact of disability status on SDI: SR scores was sensitive to the decision to use administrative data rather than self-reported data. All analyses were completed in the linear mixed modeling framework (Hoffman, 2015), accounting for nested data and the decomposition of the variance at each level of nesting (i.e., occasions were nested within students, and students were nested within schools). All models were fit using maximum likelihood estimation, which allowed for model fit comparisons with different fixed effects via loglikelihood, utilizing lme4 in R (Bates et al., 2015; R Core Team, 2019), as well as using related fit statistics such as  $\Delta AIC$  (i.e., smaller is better,  $>2$  indicates a change in fit; Burnham & Anderson, 2004). The effect size for differences between groups was calculated using Hedge's  $g$ , with interpretation following Cohen's guidelines (i.e., .2 small, .5 medium, and .8 large; Cohen, 1992).

## Results

### RQ 1: Within Data Source Differences in IEP and Disability Status

Table 2 provides a descriptive overview of responses on disability and IEP variables across self-report and administrative data sources. Within administrative data, IEP and disability status variables were almost in complete alignment. In data from the state DOE (three schools in the sample), 100% of students who had a disability coded in the data set also were coded as having an IEP. For the remaining three schools in the second state, 1.4% of cases (14 students) had a disability label coded in the data set but were

coded as not having an IEP. This may be a simple entry error in the administrative data or reflect a small sample of students that either exited from special education services or had 504 plans, although consistent data about having a 504 plan or exiting special education services were not available in any of the administrative data sources. As such, administrative data appears to primarily provide information on students who are (or are not) receiving special education services and have an IEP.

A different pattern was found in the self-report data. As shown in Table 2, a much larger number of students (12.6%) of the sample self-identified as having an IEP than did having a disability (4.4%). We calculated percentage agreement between students' report of having a disability and having an IEP, and agreement overall was only 89%, suggesting that 11% of students reported these as distinct constructs. A McNemar test comparing IEP and disability status per student self-report was significant ( $\chi^2 = 54.485$ ,  $df = 1$ ,  $p$  value  $< .001$ ), with odds ratio  $77/8 = 9.63$ , indicating a large effect, confirming that students were significantly more likely to report having an IEP than they were to report having a disability.

### RQ 2: Self-Report Versus Administrative Data on IEP Status

Given results suggested differences *within* data sources, our next step was to look at agreement *across* data sources. As shown in Table 2, per the administrative data, 17% of the sample of students were identified as having an IEP. However, in the self-report data, only 12.6% identified as having an IEP. The McNemar test indicated this difference was statistically significant ( $\chi^2 = 5.95$ ,  $df = 1$ ,  $p$  value = .015), with odds ratio  $30/13$  (2.31), indicating a medium effect with administrative data being more likely to indicate that a student in the sample had an IEP. Accounting for differing sample sizes across the two data sources (see Supplemental Table 1), nearly a quarter of students receiving special education services (29.1%) per administrative data self-reported that they did not receive special education services. As there were different rates of missingness across data sources (see Table 2), we conducted chi-square tests investigating the missing data mechanism. Results were nonsignificant, supporting the hypothesis that missing data were MCAR. Thus, there was no statistical evidence that these obtained results were biased with respect to the source of missingness.

### RQ 3: Self-Report Versus Administrative Data on Disability Status

We conducted an analysis parallel to RQ 2 for disability status to determine agreement across data sources regarding which

**Table 2.** Proportions of Disability Status, Labels, and IEP Status Relative to Total Sample for Self and Administrative Data.

Disability and IEP Variables	Student self-report		Administrative data	
	<i>n</i>	%	<i>n</i>	%
<b>Disability Status</b>				
No	874	88.3	769	77.7
Yes*	44	4.4	182	18.4
Missing	72	7.3	39	3.9
<b>If Yes* for Disability Status, Disability Label</b>				
Autism Spectrum Disorder	3	6.8	13	5.9
Deaf-blindness	0	0.0	0	0.0
Deafness	0	0.0	0	0.0
Emotional Disturbance	2	4.5	6	2.7
Hearing Impairment	0	0.0	1	0.5
Intellectual Disability	0	0.0	7	3.2
Learning Disability	15	34.1	107	48.4
Multiple Disabilities	0	0.0	0	0.0
Other Health Impairment	6	13.6	40	18.1
Orthopedic Impairment	1	2.3	2	0.9
Speech Language Impairment	3	6.8	5	2.3
Traumatic Brain Injury	1	2.3	1	0.5
Visual Impairment	1	2.3	0	0.0
Missing	12	27.3	0	0.0
<b>IEP Status</b>				
No	725	73.2	787	79.5
Yes	125	12.6	168	17.0
Missing	140	14.1	35	4.0

Note. Missing data on self-report data includes data from inconsistent student responses across the 3 time points, students skipping the question, and (in the case of IEP) the student selecting "Not Applicable." IEP = Individualized Education Program.

subset of students had a disability. As shown in Table 2, only 4.4% ( $n = 44$ ) of the total student self-report sample consistently reported having a disability whereas in administrative data, 18.4% ( $n = 182$ ) of the total sample was identified as having a disability. In other words, an estimate of the disability prevalence will increase by a factor of five using the administrative data as opposed to the self-report data. The McNemar test ( $\chi^2 = 93.13$ ,  $df = 1$ ,  $p = < .001$ ) confirmed this difference was statistically significant, with an odds ratio of  $129/13 = 9.9$  (a large effect). The chi-square test of whether a consistent response, inconsistent response, or skipping the self-report disability question was associated with administrative disability status (yes/no) was statistically significant ( $\chi^2 = 22.278$ ,  $df = 1$ ,  $p = < .001$ ). Further testing revealed that students administratively identified as having a disability were more likely to provide inconsistent responses on the standardized demographic form ( $\chi^2 = 20.69$ ,  $df = 1$ ,  $p < .001$ ). Knowing that the missing pattern in self-report

data was related to administrative disability status, particularly with respect to consistent responses over time, and thus not MCAR, we next examined the sensitivity of our McNemar results to the time of self-reported disability status report (baseline, mid-year, and end of the year) to examine for bias. We also examined if using a sample that included students who ever self-reported having a disability influenced the results. We found the direction and statistical significance of the effect via McNemar tests were the same under each of these conditions. This suggests the same conclusions would be drawn about differences across self- and administrative reports, even if different self-report criteria for disability were used. Administrative data are more likely to identify a disability, even after accounting for fluctuations in student responses over time. Ongoing research will be needed to substantiate the finding that students administratively identified as having disabilities are more likely to change their answers over time.

We followed up these analyses of disability status (yes/no) with analyses of the disability labels identified in administrative data and self-report. Table 2 provides the percentages of the total sample in the administrative and self-report data identified as having one of the disability labels recognized under IDEA as well as the number with an IEP. Descriptive analyses (see Table 3) found that more than 70% of students administratively identified as having disability labels self-reported not having a disability and almost 30% of students that self-identified as having a disability were not identified in administrative data. Therefore, as suggested by Table 3, there was substantial disagreement across data sources for any given student, particularly for those identified in any one data source as having a disability. There was also disagreement on disability labels even when a disability was identified (Supplemental Table 2 provides additional data on congruence in disability labels across data sources).

#### **RQ 4: Impact of Reporting Source on Self-Determination Outcomes**

Figure 2 provides boxplots showing the range of SDI: SR scores across the 3 measurement time points during the first year of the C-RCT based on the four different data sources (self-reported disability, self-reported IEP, administrative-reported disability, and administrative-reported IEP). SDI: SR scores for students who self-reported they had a disability differed markedly from the administrative report, whereas other sources appeared to be more similar. Given these findings and typical disability variables used in intervention studies, we chose to use the self-reported disability and administrative-reported IEP status in our sensitivity analysis. Given these decisions, the sample was constrained to contain only students with both self-reported disability and administrative IEP status data, reducing the sample to

660 students for the beginning, 621 students for the middle, and 527 students for the end of the academic year time-points. We constructed our linear mixed models to test for the impact of self-reported disability and administratively reported IEP status on self-determination outcomes over time. Various models were tested, beginning with an empty-means random intercept model (observations nested within students). The intraclass correlation (ICC) was .63, indicating that 63% of the variance was between students, and 37% was within students. A second level of nesting was added to account for dependencies at the school level (i.e., where randomization occurred). Of the 63% of the variance that was estimated to be between students, <1% was attributable to the school level. The fixed effect of time (using a piecewise effect with the mid-year as the reference) and IEP status per administrative report were then added to the model as were their interactions. A piecewise effect of time was used as previous work with data from this C-RCT (Raley et al., 2020) indicated the effect was nonlinear with there being a depression at the mid-year point. Removing the interaction terms resulted in no significant loss of fit, indicating the interaction term did not contribute meaningfully to the model ( $\Delta AIC = -3$ ;  $\chi^2 = .292$ ,  $df = 2$ ,  $p = .8641$ ). There was no main effect of IEP status as reported by administrative data on SDI: SR scores, using Wald tests with Satterthwaite's method for degrees of freedom ( $t = -1.40$ ,  $df = 767.79$ ,  $p = .162$ ). Baseline and end of year timepoints were significantly different from the reference occasion (i.e., mid-year) indicating that there were changes in SDI: SR scores, specifically they fell significantly between times one and two ( $t = 4.29$ ,  $df = 1,091.46$ ,  $p < .001$ ) and rebounded significantly at the end of the year ( $t = 3.25$ ,  $df = 1,064.11$ ,  $p = .001$ ), consistent with broader trial outcomes (Raley et al., 2020).

Next, we used the same approach to determine the impact of using self-reported disability status on outcomes. There was no interaction between time and self-reported disability status ( $\Delta AIC = 0$ ;  $\chi^2 = 3.72$ ,  $df = 2$ ,  $p = .156$ ) and the interaction was dropped from the model. There was a significant effect for each time segment, with  $t(1,089.35) = 4.332$ ,  $p < .001$  for timepoint one, and  $t(1061.67) = 3.237$ ,  $p = .001$  for timepoint 3. There was also a significant effect of self-reported disability status ( $t = -3.01$ ,  $df = 854.75$ ,  $p = .003$ ). The unstandardized effect estimate was  $-6.96$ , indicating students who self-identified as having a disability scored, on average, roughly 7 points lower on the SDI: SR than their peers who identified as not having a disability.

Finally, we directly compared outcomes across groups of students who were administratively identified as having an IEP, but who themselves did not identify as having a disability (the reference group), to all possible combinations of students identified by administrative data to have IEPs and/or who self-reported having a disability. Results of the main

**Table 3.** Number and Percentage of Student Self-Report and Administrative Data Disability Labels by Other Source's Disability Status (Yes/No).

	Student self-report disability label				Administrative disability label			
	Admin. No disability		Admin. Yes disability		Student No disability		Student Yes disability	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
No Disability	715	93.0	129	70.9	715	81.8	13	29.5
Autism Spectrum Disorder	0	0.0	2	1.1	7	0.8	3	6.8
Emotional Disturbance	2	0.3	0	0.0	5	0.6	0	0.0
Hearing Impairment	0	0.0	0	0.0	0	0.0	0	0.0
Intellectual Disability	0	0.0	0	0.0	7	0.8	0	0.0
Learning Disability	2	0.3	12	6.6	82	9.4	11	25.0
Multiple Disabilities	0	0.0	0	0.0	0	0.0	0	0.0
Other Health Impairment	4	0.5	2	1.1	22	2.5	10	22.7
Orthopedic Impairment	0	0.0	1	0.5	1	0.1	1	2.3
Speech Language Impairment	3	0.4	0	0.0	4	0.5	1	2.3
Traumatic Brain Injury	0	0.0	0	0.0	1	0.1	0	0.0
Visual Impairment	1	0.1	0	0.0	0	0.0	0	0.0
Missing Data	42	5.5	36	19.8	30	3.4	5	11.4

Note. The data presented here is linked (i.e., joint) data, and thus the counts will be necessarily different from the marginal counts in Table 2.

effects model are provided in Table 4. Students who did not have IEPs according to administrative data and who self-reported as having no disability did not significantly differ from the reference group ( $t = .25, df = 720.38, p = .806$ ), nor did students who were not identified as having an IEP per administrative data but who self-reported having a disability ( $t = -1.40, df = 919.39, p = .163$ ), although it should be noted that the sample size for this cell was only 13 (1.6% of students in analysis) and thus the confidence band was large. However, students who had IEPs per administrative data and who also self-reported having a disability had significantly lower SDI: SR scores relative to the reference group ( $t = -2.29, df = 827.08, p = .022$ ). Students in this category scored 6.8 points lower on average on the SDI: SR than did the reference group.

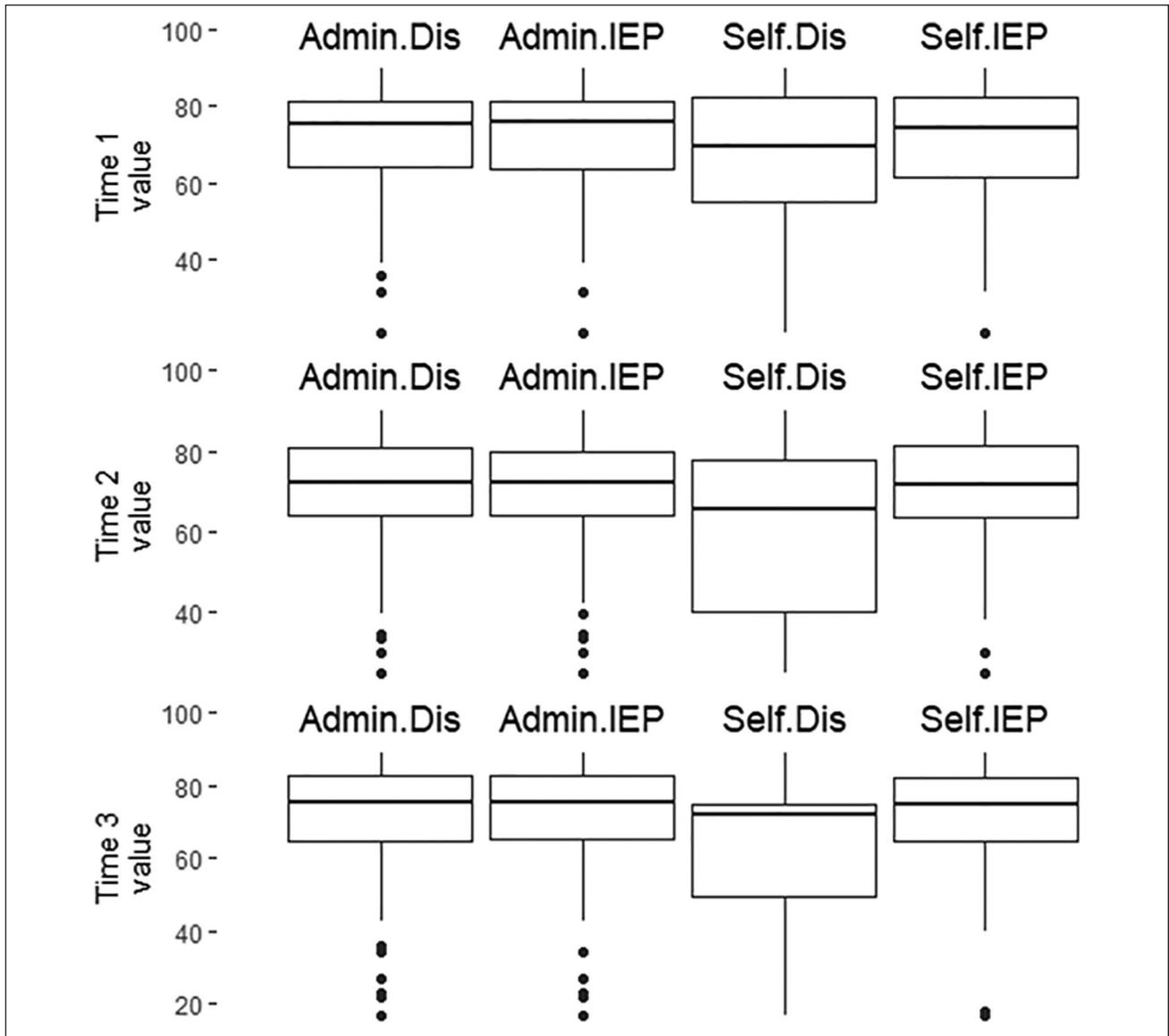
## Discussion

Researchers have consistently acknowledged divergences in disability classification based on data sources utilized and suggested these differences can lead to significant issues in defining disability populations for analyses (Honeycutt et al., 2014; Rossi et al., 1997; Wagner et al., 2007; Wittenburg & Loprest, 2007). However, this has rarely been directly examined in the secondary special education field, particularly in the context of intervention efficacy research in inclusive settings. Overall, our findings suggest there are consequential differences in reporting of disability and IEP status across administrative and self-report data that could have implications for decision-making about “for whom” interventions work in the context of

efficacy studies. Administrative data appear to reserve the term disability for students with IEPs who receive special education services. However, students tend to show greater differentiation in their reporting of their disability and IEP status. Furthermore, there is relatively low agreement across data sources on a given student's IEP or disability status. Thus, when different data sources are used to define samples in intervention efficacy research this will likely lead to different conclusions with significant implications for research, policy, and practice, as demonstrated using data from the first year of our C-RCT.

### Within Data Source Differences in IEP and Disability Status

Using data collected from almost 1,000 students, we first separately explored the degree to which there were differences *within* our two data sources on IEP and disability status. Eligibility for special education services and supports requires having an identified disability that creates a need for special education and related services. As such, students can have a disability but not qualify for special education services and supports. For example, some students with disabilities may not have an IEP, yet do have a 504 plan that details accommodations required because of the disability. In the administrative data available to us, we found high congruence between having an identified disability (18.4% of the sample) and an IEP (17.0%), with only 1.4% of students who had an identified disability in administrative data not also having an IEP—these cases only occurred in one state in our sample. This suggests high concordance in the



**Figure 2.** Plots of mean SDI:SR scores by disability or IEP source at each timepoint.

Note. SDI:SR = Self-Determination Inventory: Student Report; IEP = Individualized Education Program; Admin. Dis = administrative reported disability; Admin. IEP = administrative reported IEP; Self.Dis = self-reported disability; Self.IEP = self-reported IEP.

data variables about disability and IEP available from administrative sources. Ongoing research is needed as administrative data are often managed separately for special education, which may mean administrative data may actually underestimate disability if 504 plan or other indicators of disability status are not available. Determining the most effective ways of aggregating data from multiple sources and systems will be important to consider, particularly to define samples and meaningfully examine the various factors that might influence outcomes.

Student self-report, however, presented a very different pattern. Students were significantly more likely to identify themselves as having an IEP (12.6% of the sample) relative

to having a disability (4.4% of the sample). Most students in this study were in ninth grade, suggesting they may not yet have been receiving transition planning supports and services, which is mandated under IDEA to begin at age 16 and can focus on disability awareness, particularly in relation to requesting accommodations in future postsecondary education or employment contexts (Flexer et al., 2013). However, given that inviting students to attend and participate in IEP meetings is identified as best practice in the special education field, even if students tend to participate at low levels (Martin et al., 2006), perhaps students were more familiar with the term IEP than disability. Ongoing research is needed to replicate this finding and explore factors that

**Table 4.** Main Effects With Administrative IEP and Self-Reported Disability Status on SDI: SR.

Predictors	Estimates	CI	<i>p</i>
Intercept	77.86	[75.11, 80.61]	<.001
Time 1	2.3	[1.27, 3.34]	<.001
Time 3	1.75	[0.66, 2.84]	.002
No Admin., No SR	0.35	[-2.41, 3.10]	.806
No Admin., Yes SR	-6.13	[-14.72, 2.47]	.162
Yes Admin., Yes SR	-6.83	[-12.69, -0.98]	.022
Random Effects			
$\sigma^2$		78.73	
$\tau_{00\text{ student}}$		134.94	
$\tau_{00\text{ schools}}$		.87	

Note. IEP = Individualized Education Program; SDI:SR = Self-Determination Inventory: Student Report; CI = confidence interval; Admin. = administrative report of IEP status, SR = self-reported disability status.

might impact students' decisions around disability identification (Mueller, 2019). These differences, however, suggested that it was worth further exploring congruence across data sources to determine if data sources could influence conclusions drawn about trial outcomes.

### *Disability Status, Label, and IEP Congruence Across Self-Report and Administrative Data*

Given differences in disability and IEP status within self-report and administrative data, we examined congruence across data sources. Regarding disability status, almost four times more students were identified as having a disability based on administrative data than self-report. The magnitude of the differences suggests these could potentially be considered different populations, as suggested by other researchers working with population survey data (Rossi et al., 1997). The difference in reported IEP status across data sources was less, shaped by the higher number of students who identified as having an IEP, but the difference was statistically significant with a medium effect size. If replicated, this lack of disability identification in secondary students served in inclusive settings needs attention in research and practice, particularly efforts to promote consistency in defining samples as well as in defining "for whom" interventions are effective.

Also of interest were discrepancies related to disability labels (see Table 4); there were frequent discrepancies in the labels schools assigned to students and students' own identification. For example, 77% of students identified as having a learning disability via administrative data self-reported they did not have a disability at all. This occurred in other categories, although the counts were much smaller. Future research is needed to explore the patterns of divergence based on specific disability labels, with a particular

emphasis on students with more extensive support needs as this trial took place in inclusive classrooms and most students had relatively low support needs.

Ongoing work is also needed to examine the association between changes in student reporting and administrative data over the first year of the C-RCT. Students completed the demographic questions 3 times (baseline, mid-year, and end of year) each time they took the SDI: SR. While the overall analyses focused on students who did not change their responses, there was a small percentage of the sample, 6.5% for disability and 5.4% for IEP status, who did change. We found that students who were administratively identified as having a disability were significantly more likely to change responses in their self-report disability status (although not IEP status). This finding warrants further investigation as it could be that these students enhanced their disability awareness and changed their identification due to instruction or special education services and supports as the year went on, which could be a positive finding. It could also reflect changes in status (e.g., students diagnosed during the year, moving in or out of eligibility for special education) that were not captured in the administrative data, which reflected the point in time at which data were entered into the system. Or it could be that students did not understand or read the question thoroughly each time. Delineating if this is measurement noise (e.g., errors in entry), actual changes in student self-perceptions, or misalignment of the frequency of self- and administrative reports is critical, as when these data are captured will likely influence the disability sample used in any analyses. The lack of association for IEP status could reflect this being perceived as more stable by students and more consistent with the administrative report. More research is needed, particularly on this subgroup for whom the reports change, as such change would be rarely captured in existing data collection and analysis and could have significant implications for data collection in intervention efficacy trials.

Overall, the significantly lower levels of students who self-identify as having a disability compared with administrative data suggest the need for work understanding why these discrepancies exist, including more focus on disability identity development and how adolescents experience and navigate their disability and school-based services in inclusive settings (Mueller, 2019). Understanding these factors has implications not only for characterizing study populations but also for exploring factors that may impact student outcomes in intervention efficacy research. For example, if stigma is limiting a student's willingness to identify, how does this impact self-determination and other outcomes, and can this be accounted for in broader analyses attempting to establish evidence-based practices? Are there issues related to curriculum and support in inclusive settings that need to be further addressed and enhanced to meet student support needs?

## *Impact of Data Source on Self-Determination Outcomes*

The findings for the first three research questions confirm that in the C-RCT from which these data came, different samples can be generated for analyses based on the disability identification variables used. Administrative data on receipt of special education services through an IEP identified a significantly different and larger number of students than self-report data. This suggests it might be possible to draw different conclusions about existing group differences with respect to trial outcomes (i.e., changes in self-determination scores) based on the disability data source utilized.

We established an overall change pattern in self-determination data that reflected a small but significant decrease from baseline to the middle of the year and then a rebound to baseline levels by the end of the year linked to receipt of the SDLMI, consistent with other reporting on trial outcomes (Raley et al., 2020). This decrease at mid-year has been hypothesized to reflect students recalibrating their understanding of their self-determination abilities after initial instruction, leading to more realistic (lower) evaluations of self-determination abilities, which rebounds during ongoing instruction. When exploring if this pattern is influenced by disability, first using administrative (IEP) data, no disability effect was found. All students had similar outcomes irrespective of having an IEP. However, when using self-reported disability status, students who self-identified as having a disability reporting consistently lower levels of self-determination by almost seven points on the scale (out of 100 points) at each time point, a small effect ( $g = .46$ ). When we incorporate both data sources, we found that students who identified administratively as having an IEP and by self-report as having a disability had significantly lower levels of self-determination than did students administratively identified as having IEPs but who did not self-report having a disability.

These results suggest two key findings. First, in the present analyses, the two disability data sources (i.e., self-report and administrative data) define different disability populations. Second, depending on the data source utilized, different conclusions are drawn about self-determination outcomes in the first year of the C-RCT. Specifically, conclusions about self-determination outcomes for different subgroups (disability vs. no disability) are sensitive to the disability data source utilized. Students with disabilities only appear to have lower levels of self-determination than students without disabilities if analyses utilize self-report data. Other intervention efficacy researchers may need to consider these findings and the implications for defining samples and explicating decision making about variables adopted to define samples and infer “for whom” interventions are effective.

With respect to the potential of both sources to be used simultaneously to define disability populations, it is possible that students who are identified through both administrative and self-reported data may have more intensive instructional needs to engage in self-determination instruction. Without the inclusion of both sources of information in defining the study population, this variability would not be identified. Such information could highlight factors that should be considered in identifying student groups that may be at higher risk of poor outcomes. Overall, the findings suggest researchers should not only more fully describe and justify the variables they use to define disability in intervention research, but also consider the use of variables from multiple data sources to more accurately predict outcomes (Burkhauser et al., 2012).

## *Limitations*

There are several limitations that must be considered in exploring these findings. First, this analysis uses data from 1 year of a 3-year C-RCT, where students and schools are being phased in over time. For this reason, the sample size and outcome data are limited. Second, the focus of our analysis was to explore how students identified as having a disability by administrative or self-report may constitute different groups, and how these differences may impact conclusions drawn about the primary outcome variable in our C-RCT (i.e., self-determination). Ongoing work is needed to directly test the impact of disability data source on conclusions about intervention effects (i.e., impact of differing intensities of supports for teachers implementing the SDLMI) as well as how other important covariates (e.g., gender, age, and race) influence outcomes. Relatedly, the veracity of the disability and IEP status differences found in this study needs to be examined in other work to determine the replicability of the findings across intervention efficacy trials. Even with these limitations, however, the current findings provide initial and rarely discussed implications and directions for future secondary intervention research.

Third, we do not have data to more robustly explore the factors that might predict differences in reporting. For example, as noted in the section on administrative data, determining where and how other sources of data might be captured was challenging, because even within one administration system (i.e., education) there are multiple systems and purposes for which data is collected. In addition, we did not assess students' understanding of terms such as “disability” and “IEP” as they responded in the online system. Although the general consistency in responding across the 3 time points in the large majority of the sample suggests that students were responding in similar ways to items, there were likely many other factors that influenced responding. While we explored sensitivity to different decisions

in handling missing data in student responses, the cause of students not responding to items about disability status was unknown. Furthermore, our sensitivity analysis for missing data allowed us to determine that different methods of handling the missing data resulted in similar findings, but it is impossible to say whether any method would align with results gleaned from data that was entirely complete. Thus, the missing data pattern and incongruence in reporting over time are potentially a limitation of this data set, and the cause and impact of such missing data should be explored in ongoing research. Additional exploration using mixed methods or qualitative examination of how secondary students who are receiving most of their instruction in inclusive, general education classes perceive both their disability status as well as the special education services and supports they receive through an IEP is needed.

In addition, we did not explore the perceptions of other key stakeholders, namely the general and special education teachers who were delivering SDLMI instruction. The degree to which they agreed a given student had a disability or IEP based on their area of expertise (i.e., general or special education) and the congruence with student perceptions and administrative data would have been informative for the inclusive education field. Future research in this area could begin to determine the degree to which self-perceptions of disability or knowledge of administrative classifications influence teacher behavior and student outcomes. For example, for students who self-identify, one interpretation could be that students are more aware of their learning needs and are more accurate in their reporting. However, another interpretation could be that students have been stigmatized and had negative experiences that reduced their outcomes because they are perceived by others as having a disability. More work is needed to explore these factors and perceptions across students, teachers, and the impact this has on administrative data, instruction, and supports in inclusive general education classrooms, student identification, and outcomes. Finally, we stress that the results presented in this analysis are exploratory. We sought to investigate the potential sensitivity of the data source used to define disability and IEP status with respect to self-determination outcomes in the first year of the larger C-RCT. Therefore, the effect sizes and tests of significance reported in this paper should be used primarily to indicate the existence of sensitivity to the source of disability information and not used as evidence for any particular group differences. Future research is needed to confirm these results using confirmatory methodologies with additional data collected by other research groups. Linear mixed models were used to account for variability due to the nesting of observations within students, and students within schools. A multi-level structural equation modeling framework would have also additionally allowed for an accounting of error due to

measurement. However, due to the small number of level-2 units (i.e., 6 schools) this approach was not feasible (see, McNeish, 2017). Future research with a more robust level-2 cluster size will be needed to test these findings in a latent modeling framework.

### ***Overall Implications for Future Research, Policy, and Practice***

The findings of the present study suggest that the disability identification variables used in intervention efficacy trials could have significant implications for the conclusions drawn about the subpopulations for whom interventions are effective. Future research should investigate the impact of using different disability data sources on the effect estimates for interventions targeting students with and without disabilities in inclusive general education classrooms. Guidelines are needed for reporting on how decisions are made about disability-related variables used in analyses. In addition, the combined power of self-report and administrative data in defining samples and predicting outcomes must be further considered. It is highly probable that, particularly in secondary education, perceptions of disability influence outcomes, perhaps in unique ways, above and beyond special education service receipt. Self-perceptions are increasingly recognized as a variable that is critical to explore rather than only relying on “objective” or external data sources. Future research is needed to explore how disability self-identification, particularly when associated with identity and empowerment, can be a source of strength and community as well as how choosing not to self-identify can be protective when negative, structural factors (e.g., stigma and segregation) are present classrooms and schools. The perceptions of others, including teachers, family members, and peers must also be considered.

For researchers and policymakers who are increasingly focused on inclusive instruction and establishing effective universal, Tier 1 interventions, it will be necessary to consider how differing factors may influence student perceptions and engagement in their learning as well as the degree to which disability-related variables and the intersections of disability with other personal factors (e.g., race/ethnicity and gender) are informative in studying these issues. Ultimately, the preliminary findings reported here suggest that, at a minimum, greater consideration should be directed in intervention efficacy research to engaging in sensitivity analysis to inform decision-making about disability variables used to define samples. Ongoing work should also explore the more complex issue of integrating multiple perspectives of disability into analyses of intervention outcomes and the role of such information in identifying factors that predict response, allowing for a more nuanced understanding of “for whom” interventions are effective.

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## Supplemental Material

Supplemental material is available on the webpage with the online version of the article.

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