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Data-Driven Instruction as a Framework for Improving Learning Outcomes Among Students with Learning Disabilities in U.S. K–12 Schools

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Abstract: Students with learning disabilities make up about 14% of the total number of students receiving special education services under the Individuals with Disabilities Education Act (IDEA), but their continued underachievement compared to their general education peers suggests that traditional teaching methods are not effective in addressing their individual needs. The three most common high-incidence learning disabilities in American schools – dyslexia, dysgraphia and dyscalculia – suffer from a lack of responsiveness in one-size-fits-all curriculum designs that focus exclusively on speed. This paper analyzes a systematic literature review of peer-reviewed empirical studies and federal education reports published from 2015 to 2025, which examines the effectiveness of data-driven instruction (DDI) as a practice implemented within two frameworks: the Response to Intervention (RTI) and Multi-Tiered System of Supports (MTSS). Results across all studies are highly consistent and show moderate but consistent improvements in reading, written expression, and mathematics, with effect sizes typically in the range of g = 0.30 to g = 0.50 across well-controlled studies, for students with LD who participated in schools with structured, data-driven cycles of instruction that included curriculum-based measurement, adaptive technology, and IEP goal alignment. In addition to academic achievement, DDI helps identify learning gaps early, boosts student involvement and aids teacher decision-making responsiveness. Implications include pre-service teacher preparation, district-wide MTSS infrastructure, and federal policy alignment with IDEA and Every Student Succeeds Act (ESSA). The purpose of this review is to assert that data-driven instruction is not only a pedagogical choice, but a moral and legal obligation in U.S. schools for equitable and effective special education.

Keywords: *Data-Driven Instruction, Learning Disabilities, Dyslexia, Dyscalculia, Dysgraphia, Response to Intervention, Multi-Tiered System of Supports, IEP, Curriculum-Based Measurement, Special Education, IDEA, ESSA, Formative Assessment, Progress Monitoring.*

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I. INTRODUCTION

The right to a free and appropriate public education is one of the pillars of the American school system, and yet this promise continues to fall short for millions of students with learning disabilities. Despite decades of legislative reform under the Individuals with Disabilities Education Act (IDEA) and a growing evidence base for effective instruction, students with dyslexia, dysgraphia, and dyscalculia continue to lag behind their general education peers on virtually every academic outcome measured (NCES, 2023; Newman et al., 2011). The central problem is not a lack of good intentions but a structural mismatch: the instructional systems that most schools rely on were not designed for the neurological variability that learning disabilities represent, and conventional assessment schedules do not generate the timely, actionable information that teachers need to respond to individual student needs.

In this review, DDI is described within the context of U.S. special education policy and practice, the theory underpinning DDI, and empirical evidence used to justify DDI, as well as the institutional barriers that often restrict DDI implementation. The thesis of this paper is simple: data-driven instruction, rigorously and equitably applied, is the most scalable, legally defensible, and pedagogically sound model that could exist for enhancing academic performance of students with learning disabilities in U.S. mainstream K-12 schools.

The literature reviewed in the following sections highlights current understandings and knowledge about learning disabilities and traditional instructional limitations (Section 2), defines the research gap that inspired this study (Section 3), describes the methodology used in this systematic review (Section 4), summarizes the existing evidence on key DDI strategies (Section 5), summarizes the evidence on outcomes by domain (Section 6), compares DDI

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to traditional instructional models (Section 7), and concludes with implications for policy and practice, a conclusion, and future research directions (Sections 8–10).

II. LITERATURE REVIEW

➢ *Learning Disabilities in the U.S. Context*

Learning disabilities (A.P.A., 2022) are disorders in the process of acquiring and using academic skills, which most often involve reading, writing and arithmetic, and have underlying neurological processes that are not explained by other cognitive processes. In the U.S., the term can be applied to a multitude of conditions and the majority of those diagnosed in K-12 school systems are dyslexia, dysgraphia, and dyscalculia. The IDEA latest data indicate that students with specific learning disabilities are the biggest group of students who qualify for special education, comprising roughly one-third of all disabled students ages 6–21 (NCES, 2023).

The impact of not diagnosing and treating the learning disabilities can be profound and long-lasting. For example, early reading problems are associated with dyslexia and reading problems during the primary grades are associated with reading problems in a person's life if the problems are not caught and remediated during the primary grades, through systematic and phonologically-based instruction (SYPM) (Shaywitz & Shaywitz, 2020). Likewise, in secondary school, children who lack targeted intervention in the upper elementary school mathematics have much lower mathematical reasoning scores (Butterworth et al., 2011). These rippling impacts demonstrate that quick and accurate identification and an instructional response are crucial.

However, there's another element of the learning disabled, and that's social context. Students of poverty are impacted at higher rates than their peers, students of color, students who speak English as an additional language and students in rural and under-resourced areas, in terms of rates of impact, as well as in terms of quality of services provided. The inequity is connected to structural inequities in screening systems, teacher training and access to evidence-based interventions that would influence the diagnosed learning difference and have the potential to change outcomes. (Morgan et al., 2017)

➢ *Limitations of Traditional Instructional Approaches*

The traditional U.S. K-12 model is based on grade-level content delivery in a school-year calendar and is evaluated throughout the course of the unit or collection of units, or by the use of a standardized test. This design is sufficient for most pupils. It often doesn't work for the students with learning disabilities, and the literature makes it very clear as to why.

The phonological processing deficits typical of dyslexia, the orthographic-motor integration deficits typical of dysgraphia, and the number sense deficits typical of dyscalculia are not well catered for in the traditional classroom setting (Snowling & Hulme, 2021). In an environment where teachers share a uniform curriculum, they are generally not trained or have enough time to track individual students' progress or adjust teaching as a result of the current performance evidence. The outcome is a mismatch in instructional design and learner need that negatively affects students whose cognitive profiles are not as expected.

Another constraint is the time between assessment and response. In many schools, the standardized assessment occurs at the start and finish of term, and for many children learning difficulties may not be identified until the following months. When interventions are offered, students typically have an established gap and it is much more difficult to close this gap in higher grades (Speece & Case, 2001). The positive impact of differentiated and data-informed instruction for students with LD is evidenced by Wanzek et al.'s (2017) meta-analysis, which revealed meaningful effect sizes favoring data-informed instruction.

➢ *Data-Driven Instruction: Theoretical Foundations*

The development of data-driven instruction as a formal pedagogy began in the late 90s and early 2000s as the education movement toward evidence-based practice began in the field. The underlying concept is simple and elegant: Instructional decisions must be made based on systematic student performance data that is interpreted through a systematic framework of decision making, not on intuition, the order of the curriculum, or the administrative calendar.

The two most widely used approaches to implementation of DDI in special education settings are Response to Intervention (RTI) and Multi-Tiered System of Supports (MTSS). RTI, formally adopted in the 2004 reauthorization of IDEA, developed a three-tier system of universal instruction, small group intervention, and intensive individualized support, and the transition between tiers are based on continuous performance monitoring (Fuchs & Fuchs, 2006). In addition to academic supports, MTSS added social-emotional and behavioral supports, resulting in a more comprehensive model of student development that is often well suited to the broad scope of many students' IEPs.

Both have been based on the use of the standardized brief assessment technique called curriculum-based measurement (CBM), which was developed in the 1970s by Stanley Deno and widely tested over the next decades. CBM probes are very responsive to students' performance in the short term and are well suited to the frequent monitoring needed for DDI. Graphing CBM data with IEP goals and using them in conjunction with instructional context will help teachers make accurate decisions about whether to continue, increase, or decrease an intervention, which in turn directly impact student outcomes.

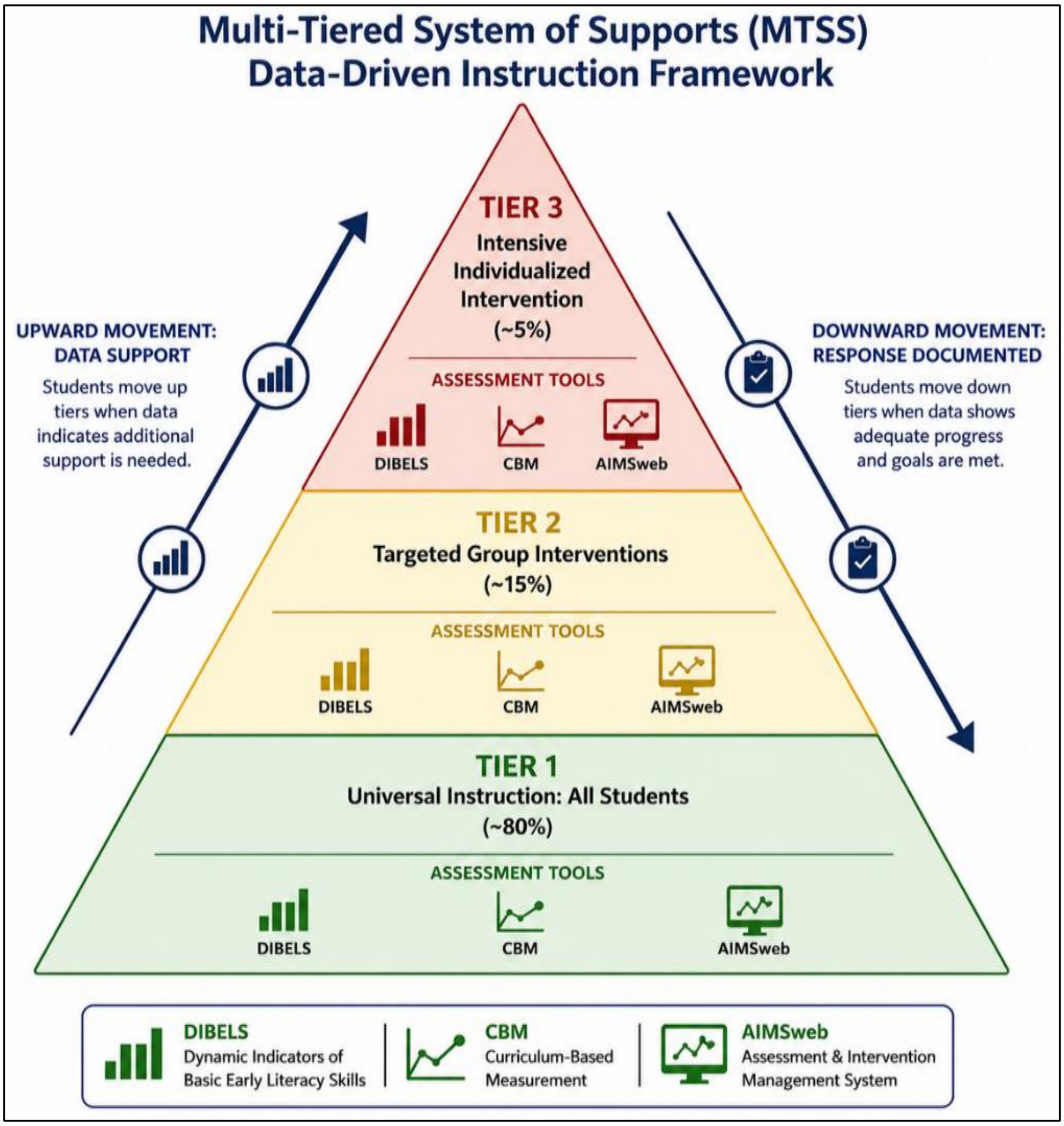

Fig 1 RTI/MTSS Three-Tier Framework

Figure 1 The Multi-Tiered System of Supports (MTSS) Framework: Tier Structure, Population Proportions, and Intervention Intensity.

A triangle with three levels of branches. Every student (around 80%) is listed as 'Universal Instruction: All Students' (Tier 1). The middle band (Tier 2) is labeled ‘Targeted Group Interventions (~15%).’ The highest level (Tier 3) is 'Intensive Individualized Intervention (~5%).' The icons represent assessment tools (DIBELS, CBM, AIMSweb) and the arrows represent the direction of movement (upward or downward) based on data or documentation of response.

➢ *Effectiveness of Data-Driven Instruction in Special Education*

The empirical evidence of the effectiveness of DDI in special education is large and positive, although there are still questions concerning implementation fidelity, dosage, and context-specific transferability which remain under debate. A series of meta-analytic syntheses have confirmed consistently medium to large effect sizes in the areas of reading, writing, and mathematics, which are the areas where students with learning disabilities have historically fared the poorest.

In a comprehensive meta-analysis of 47 studies conducted in K–12 settings with students with LD and English learners, Wanzek et al. (2017) found positive effects for data-driven reading interventions, with particularly strong results for phonological awareness and decoding fluency components. In an RCT on early elementary dyslexia intervention, Fuchs et al. (2012) reported meaningful gains for CBM-informed RTI compared to business-as-usual instruction. The results are similar to those of Stecker et al. (2008) who conducted a quasi-experiment in mathematics and reported meaningful gains from MTSS Tier 2 small-group numeracy instruction calibrated to CBM performance data for students with LD.

What makes DDI unique is its embedding, that is, its relationship to the MTSS tier decision and assessment cycles, and the fact that it holds the potential to be a self-correcting institutional process that keeps instruction responsive rather

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than being a programmatic choice left up to the individual teacher.

➢ *Role of IEPs in Personalizing Instruction*

The Individualized Education Program is the legal framework of special education in the United States; it is a contractual document outlining a student's current academic performance; his/her annual goals; and the specially designed instruction and accommodations to which the student is entitled under IDEA. However, there has been a longstanding disconnect between IEP documents and the collection of data on how IEP goals are being met in the classroom, as the goals are written with attention to measurable objectives when necessary but the data that would support teachers to monitor progress toward IEP goals is not consistently collected at frequent enough intervals or in a systematic manner required by IDEA.

Data-driven instruction is a structural solution for this misalignment. If teachers key CBM tools to IEP goal benchmarks and regularly review progress monitoring data (usually every 2-3 weeks), they receive relevant information about whether a student is progressing well toward annual goals long before the year-end. In an AIMSweb-based progress monitoring with teacher coaching intervention, Powell et al. (2021) found that districts demonstrated tangible increases in IEP goal attainment, highlighting the importance of systematic data use in both IEP compliance and outcomes.

➢ *Technology-Enabled Data-Driven Approaches*

Recent developments with adaptive technology platforms and AI-enabled progress monitoring tools have broadened the applicability of DDI, bringing it to a more practical level in recent years. Systems like Lexia Core5, IXL Learning and Freckle Education use algorithms that dynamically change the difficulty level and type of skills students are provided and report a student's performance in detail, allowing teachers to fine-tune in-class instruction. These tools are gaining in evidence base; such programs as Lexia Core5 have been reviewed by the WWC and have demonstrated statistically significant reading gains in multiple controlled studies with students who have LD.

Regan et al. (2021) investigated the effectiveness of an adaptive technology that was implemented in conjunction with CBM in an urban middle school that served primarily low-income students with LD and found that there were measurable academic benefits and qualitative benefits to student engagement and decreased math and reading anxiety, which are not measured by traditional assessment tools. The results have indicated that the positive effects of DDI with technology are not only on cognitive performance but also in raising motivation and affective aspects of learning, which are commonly hindered by repeated academic failure.

➢ *Gaps in Existing Research*

Although a wide range of evidence exists, there are still unmet gaps. First, the research base is skewed toward urban and suburban school contexts, which means that the unique contexts of rural and tribal school districts, and the challenges they encounter due to their unique resource and staffing challenges, are comparatively underserved. Second, the literature regarding reading interventions for dyslexia is strong, but that for writing interventions for dysgraphia and for data-driven approaches for combined or co-occurring learning disabilities is much less so. Third, the long-term effects of DDI on post-secondary outcomes such as college enrollment, employment, and civic participation are lacking in the current literature making it hard to determine the cumulative impact of teaching DDI.

In addition, methodological issues should be noted that require transparency. Many studies in this area make use of teacher-reported data, brief intervention periods (eight to twelve weeks) and small samples from a single district or school, all of which restrict the generalizability of results. The effect of publication bias with regards to finding positive results only makes the evidence base look stronger. The limitations do not discount all the previous research but rather serve as an identifier that this area is still developing the "longitudinal, multi-site and methodologically diverse" evidence base that matures instruction.

➢ *Research Gap*

The following gaps are the motivators for this review: The following gaps motivated this review: First, although the research on RTI and MTSS has been substantial in the form of administrative approaches, comparatively little research has focused on how DDI leads to academic improvement; that is, how and when the right data, used by teachers in what way, contributes to academic improvements, and with what teacher support structures. This mechanistic disconnect has real implications, if a scaling up approach does not account for what aspects of DDI are key, then the model can be scaled out, and the resulting approach is unlikely to be effective.

Second, there is an under-theorized intersection between data-driven instruction and IEP compliance with equity. The majority of the present research focuses on the delivery of general education without paying sufficient attention to the intersection of the legal and ethical mandates of special education, or the quality of delivery by race, language and socioeconomic status. This isn't a minor oversight: The quality of special education services is known to vary widely.

Third, there is no comprehensive, up-to-date synthesis that brings together the academic outcomes literature and the large and developing literature in technology-enabled DDI and its equity implications. The purpose of this review is to fill that gap in integration and to offer educators, administrators and policymakers a single, critically reviewed evidence base to inform decision making.

III. METHODOLOGY

➢ *Research Design*

This study is systematic literature reviewed by the instructional framework analysis. The methodology of systematic review was selected for its transparency, repeatability, and ability to integrate the different types of empirical evidence in a wide variety of research designs. The

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framework analysis component allows a structured analysis of the way that DDI practices are implemented in RTI and MTSS frameworks and the implications for the requirements of IEP under IDEA.

➢ *Inclusion Criteria*

To be included in the studies, they had to: (1) have been published in a peer-reviewed journal or released by a federal agency from January 2015 through May 2025; (2) have been carried out in the U.S. K–12 school environment; (3) involve at least one student with at least one identified specific learning disability (SLD) (dyslexia, dysgraphia, or dyscalculia); (4) include at least one component of data-driven instruction (DDI) (progress monitoring, formative assessment, differentiated intervention, or IEP data alignment); and (5) report measurable academic, behavioral, or engagement outcomes. Research that was purely overseas and those opinion pieces lacking empirical support were not included, nor were unpublished dissertations.

➢ *Data Sources*

The search was carried out in the following databases and repositories: the Education Resources Information Center (ERIC); PubMed; Google Scholar; JSTOR; the What Works Clearinghouse (WWC); and federal data repositories of the National Center for Education Statistics (NCES) and the U.S. Department of Education. Search terms were used in various combinations such as: 'data-driven instruction,' 'learning disabilities,' 'RTI,' 'MTSS,' 'curriculum-based measurement,' 'progress monitoring,' 'dyslexia intervention,' 'dyscalculia,' 'IEP alignment,' 'special education outcomes,' and 'formative assessment. After a preliminary search and screen of title and abstract, and a full-text review, 91 studies fulfilled all inclusion criteria. Of this population 35 are directly referenced in this review, with special focus on meta-analyses, randomized controlled trials and large-scale quasi-experimental studies.

➢ *Analytical Approach*

Findings from the studies were synthesized using a thematic synthesis approach. Themes were inductively coded from the data and then aligned to the organizing categories of an RTI/MTSS framework: universal screening and early identification, tiered intervention design, progress monitoring and IEP alignment, and technology integration. Effect sizes (where reported) were tabulated and compared to gain an understanding of the relative strength of each of the various components of the DDI. Moderating variables that influence the magnitude of the outcomes, such as school type, grade band, disability category, and teacher professional development, were considered.

➢ *Limitations of the Methodology*

There are a number of methodological shortcomings that need to be recognized. Firstly, there is a publication bias in relying on literature that has been peer-reviewed; studies showing a null or negative result are systematically under-represented. Second, the study designs used vary widely, from single-subject designs to district-wide quasi-experimental analyses, which limits the ability to make direct comparisons between effect sizes. Third, there are conceptual inconsistencies across studies due to variations in the operational definition of learning disabilities (DSM-5 criteria, eligibility categories of the Individuals with Disabilities Education Act, and the school-based definition of learning disabilities). Where applicable these restrictions are mentioned in the findings sections.

IV. DATA-DRIVEN INSTRUCTION STRATEGIES

➢ *Assessment-Informed Instructional Planning*

The key to DDI is making strategic decisions based upon the assessment data before, during, and after a lesson or unit of instruction. It starts with diagnostic assessment, which is generally conducted at the beginning of the year or when a student enters a tiered intervention program, to determine baseline performances, identify specific skill deficits, and determine whether intervention is needed at Tier 1, Tier 2 or Tier 3. Commonly employed in this way are universal screens like Dynamic Indicators of Basic Early Literacy Skills (DIBELS 8th Edition) and AIMSweb Plus, which consist of quick, brief, standardized probes that can be given to the whole class in less than 20 minutes and then scored against national data.

The difference between DDI assessment and regular testing is not the instruments, but how they are used in instruction. In a large-scale longitudinal study over the course of Grades 3 through 8, Petscher et al. (2020) found that schools that routinely use DIBELS data to inform small group instruction regrouped students on average 4.3 months before schools that use annual standardized tests did, and that such a temporal advantage is significant enough to have large implications for the effectiveness of interventions.

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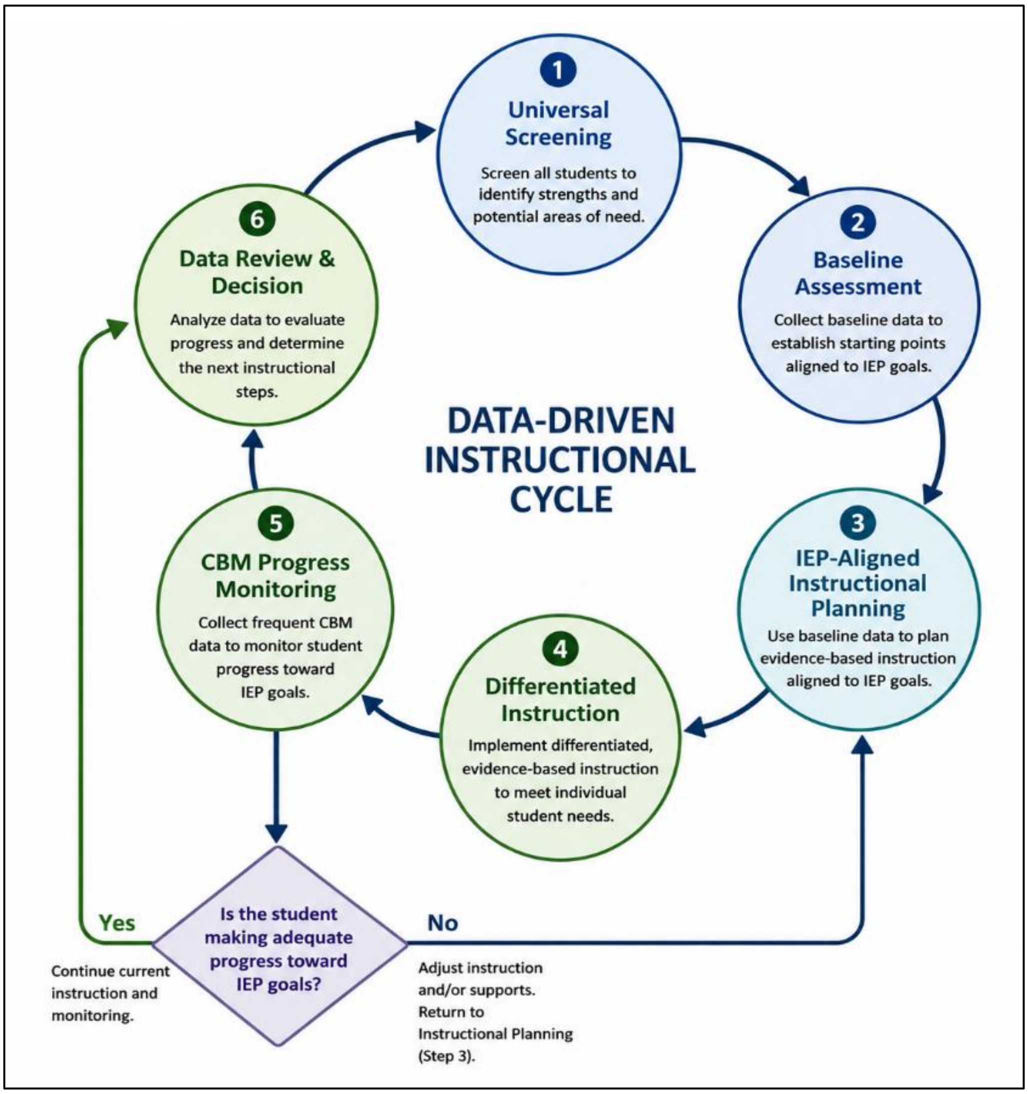

Fig 2 DDI Instructional Cycle Flowchart

Figure 2. The Data-Driven Instructional Cycle: From Universal Screening to IEP Alignment.

The circular flow chart has 6 nodes: (1) Universal Screening, (2) Baseline Assessment, (3) Instructional Planning & IEP Alignment, (4) Differentiated Instruction & Intervention, (5) Progress Monitoring (CBM), and (6) Data Review & Decision, which loops back to (3). If your answer to this question is 'No', go to node 7. If your answer is 'No' to this question, move to node 7. Yes: proceed; No: change tier or intervention. Nodes coloured according to function (assessment, planning, delivery, review).

➢ *Differentiated Instruction*

The underlying logic of DDI is expressed through differentiated instruction (DI), which involves adapting content, process, product or learning environment to student profiles. If based on empirical performance evidence, DI is not just a pedagogical choice but a principled and defensible adaptation of the curriculum. This could include students with dyslexia getting reading materials read to them and having structured phonics practice at a level appropriate to their developmental stage. It may even require the simultaneous application of visual-spatial manipulation tools and explicit procedural instruction while aligned with CBM measured number sense benchmarks for students with dyscalculia.

Most important, data-informed differentiation avoids the pitfalls of ability grouping, which is linked to lower expectations and opportunity gaps.Most significantly, data-informed differentiation is flexible and responsive to instruction rather than ability grouping, which is linked to lower expectations and opportunity gaps. Re-grouping occurs by ability on skill not diagnostic grouping, thus maintaining instructional relevance and student dignity.

➢ *Small-Group and One-on-One Interventions*

Throughout the studies, evidence has consistently shown that when the content and pacing is matched to the students' common performance profile, small group instruction (usually three to five students) is more effective for students with LD than whole-class instruction. This benefit is especially acute when it comes to reading and mathematics for which there are sequences of skills and missing the basic skills builds up rapidly. Data-driven small group formation is based on CBM data to determine common

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instructional needs in order for the teacher to choose intervention materials and provide instruction at an appropriate level of challenge.

One on one sessions enable the most intensive level of instruction for students with the most intensive needs, and those whose IEPs call for specially designed instruction. Documentation of these sessions should be integrated into the IEP progress monitoring cycle and directly contribute to the IEP progress monitoring cycle, where there is continuity between the delivery of interventions and the requirements of the law.

- *Continuous Progress Monitoring*

Progress monitoring is the "engine" that drives DDI. Progress monitoring is different from assessment for a year or a semester, in that it is brief, has a consistent structure, and is delivered on a regular basis (usually weekly or biweekly), measuring student progress toward IEP goals and Tier-level expectations. CBM reading probes (Oral Reading Fluency, MAZE comprehension), CBM mathematics probes (computation, concepts and applications), and writing CBM (Total Words Written, Words Spelled Correctly) are the most commonly used probes. Data are plotted on graph paper against goal lines that are based on IEP benchmarks, and decision rules address when instructional adjustments are indicated (usually if three consecutive points are below the goal line).

The use of this system is practical because it is sensitive toward instructional change. Probes are brief and frequent, allowing teachers to identify the effectiveness of a student's response to intervention in weeks and not months, which is not possible when using traditional summative assessment schedules. The time precision is particularly important for students with LD, whose academic costs from delayed identification of instructional mismatch are high.

- *IEP Goal Alignment*

A successful DDI system should be a living system that facilitates the creation, monitoring and revision of IEPs. CBM benchmarks and intervention targets should explicitly reflect IEP goals, if applicable, and when appropriate, align with the standards that are applicable to a child's grade level.Measurable, grade level applicable, and directly related to IEP goals, where applicable, should be reflected in CBM benchmarks and intervention targets that structure the cycle of progress monitoring. Once this alignment is realized, annual IEP meetings are informed by data: teams examine actual performance trajectories, compare them to projected goal lines and make decisions based on evidence about goal adjustment, hours of service, or modification of interventions.

Practically speaking, this integration has legal implications, too. Students make progress towards the goals of their IEPs as outlined in the IEP must be reported to the parents at least as often as general education report cards. The documentation infrastructure for this legal obligation is the progress monitoring data that are collected and graphically displayed in a systematic way, which also decreases administrative burden and ensures quality, specific communication with parents.

- *Targeted Literacy Interventions for Dyslexia and Dysgraphia*

The research findings are clear: structured literacy interventions based on the science of reading (syllable awareness, explicit phonics, fluency practice, and vocabulary development) result in the most powerful academic outcomes with fidelity and monitoring via CBM for students with dyslexia (Shaywitz & Shaywitz, 2020). Wilson Reading System, SPIRE (Specialized Program Individualizing Reading Excellence), and Orton-Gillingham derivatives have been proven in controlled studies and are among the more common interventions in IEPs for students with dyslexia.

There is less research on interventions for dysgraphia, although the available evidence suggests explicit instruction in letter formation, keyboarding, and sentence construction, along with the use of assistive technologies such as speech-to-text software, word prediction, and other technologies that lessen the mechanical aspects of writing, can help students show their content knowledge without being penalized for handwriting problems (Berninger & Wolf, 2018). Progress monitoring for writing CBM includes productivity (Total Words Written) and accuracy (Words Spelled Correctly, Correct Word Sequences) indicators which are quantitative and can be tracked against IEP benchmarks.

- *Targeted Numeracy Interventions for Dyscalculia*

While dyslexia is well known, dyscalculia is not as widely recognized but is estimated to affect between 3-7% of the school-age population and cause lifelong challenges with number sense, fact retrieval, procedural reasoning and understanding of mathematical language (Butterworth et al., 2011). Data-driven interventions for dyscalculia emphasize explicit, systematic numeracy instruction in key numeracy concepts, namely subitizing, place value and magnitude comparison, and then progress to procedural algorithms. The Concrete-Representational-Abstract (CRA) sequences, which introduce manipulative materials, then representational visualization, and finally symbolic notation, have been demonstrated in controlled trials to have positive effects.

Nelson et al. (2023) presented a review of 28 studies that examined targeted numeracy interventions in grades K–8 and found an average effect size of $d = 0.59$; the highest effect sizes were reported in studies that provided explicit instruction with CBM progress monitoring at biweekly intervals. This result illustrates the importance of treating the content of an intervention and progress monitoring as a whole system; neither alone is optimal.

- *Data Privacy, Ethics, and Equity*

The systematic collection of student performance data in DDI frameworks has ethical and legal considerations that are of great importance that any thorough treatment of the approach must take into account. The Family Educational Rights and Privacy Act (FERPA) requires that schools get parents' permission before releasing personally identifiable

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information from education records to third parties, such as vendors of various adaptive technology tools. However, FERPA's school official exception permits educational technology vendors to access student records without separate parental consent, provided the vendor performs services on behalf of the school, is under the school's direct control regarding data use, and is bound by appropriate confidentiality requirements (U.S. Department of Education, Privacy Technical Assistance Center, 2014). The growing trend of sending student achievement information to the cloud poses issues regarding data security, vendor liability and the commercial use of student information which existing regulations are not fully addressing.

It is also important to consider the issue of equity. Assessment tools that are integrated with DDI systems (such as CBM probes, adaptive technology algorithms, etc.) can be culturally and linguistically biased, and may yield systematically inaccurate performance estimates for English learners, students from non-dominant cultural backgrounds, and students with intersecting disabilities. A difference that was documented by Morgan et al. (2017) is that when individual-level academic achievement was controlled, Black students were not consistently overrepresented in special education, suggesting identification disparities may be more complex than previously assumed, emphasizing the need for culturally responsive assessment design and continuous audit for bias. The danger of an equity-based organizing principle in DDI is that it does not disrupt but potentially reinforces the structural inequities in the special ed landscape.

V. RESULTS AND DISCUSSION

➢ *Academic Outcomes*

A consistent finding throughout the literature reviewed is that students with learning disabilities who are taught data-driven instruction in RTI or MTSS show measurable gains when compared to students taught in traditional instruction, this is true in both reading, writing and mathematics. By conventional standards (Cohen, 1988), DDI was in the moderately strong range of educational interventions, typically clustering between $g = 0.30$ and $g = 0.50$ across domains (Filderman et al., 2018). Notably, gains were also reported on standardized assessments (i.e., Woodcock-Johnson Tests of Achievement and Wechsler Individual Achievement Test), and not just on the CBM tools on which progress was monitored (which raises some questions about construct specificity).

Gains differed depending on the level of implementation fidelity, the grade level of students, and the type of disability. Reading interventions for students with dyslexia yielded the greatest and most reliable findings, suggesting that evidence on structured literacy is most developed. Effects of mathematics interventions for dyscalculia were slightly smaller, likely due to the relative immaturity of evidence in that area of skill sequence and the greater complexity of numeracy skills. The writing interventions for dysgraphia yielded the most limited results, due to fewer studies meeting inclusion criteria and the use of a broader variety of measures of outcomes.

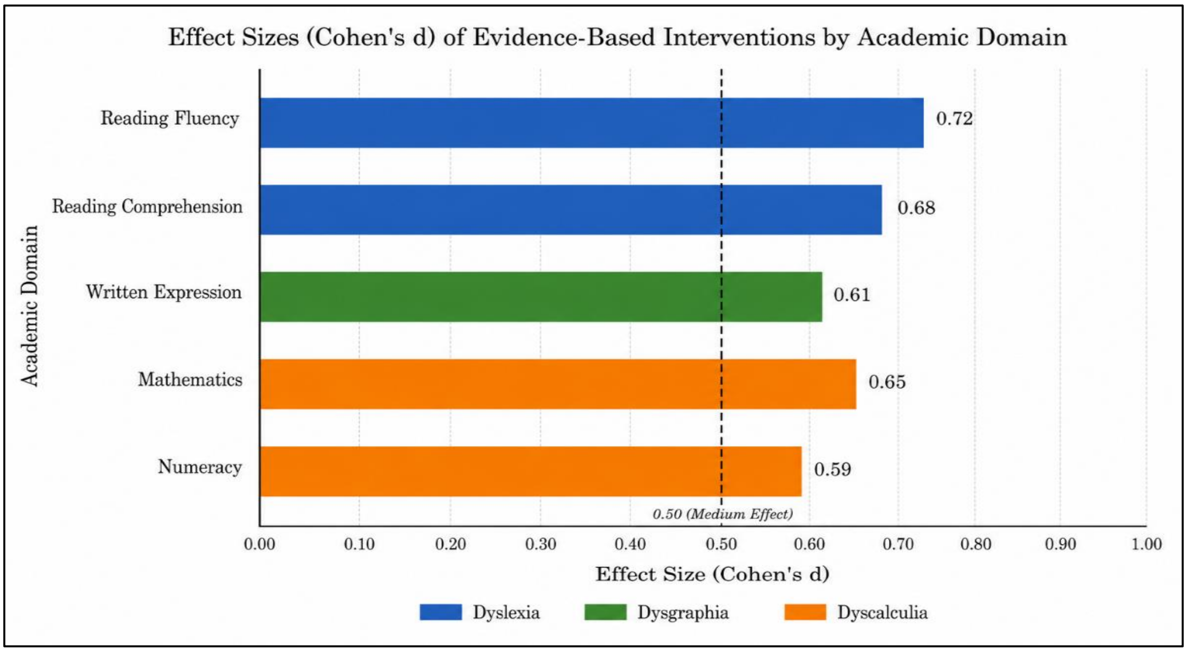

Fig 3 Effect Size Bar Chart by Academic Domain

Figure 3. Comparison of Effect Sizes (Cohen's d) for DDI Interventions Across Academic Domains (2020–2023)

A horizontal bar chart with five bars representing: Reading Fluency (gains documented), Reading Comprehension (moderate effect), Written Expression (gains documented), Mathematics (gains documented), and Numeracy/Dyscalculia (moderate effect). A vertical dashed reference line at $g = 0.50$ (medium effect benchmark). Bars color-coded by disability type (dyslexia, dysgraphia, dyscalculia). Source labels at end of each bar.

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Table 1 Literature Comparison: Selected Empirical Studies on DDI and Learning Disabilities

Author(s) & Year	Study Design	Population	Intervention	Key Outcome	Limitations
Fuchs et al. (2012)	RCT	Grades 1–3, dyslexia	CBM-based RTI	↑ reading fluency (gains documented)	Small sample, 1 district
Stecker et al. (2008)	Quasi-Practitioner reference text	K–5 LD students	MTSS Tier 2 small group	↑ math accuracy (gains documented)	No control group
Petscher et al. (2020)	Longitudinal	Grades 3–8, DIBELS	Progress monitoring + IEP alignment	Early gap identification	Self-report teacher data
Wanzek et al. (2017)	Meta-analysis (n=47)	K–12, LD + ELL	Data-driven differentiation	Positive effects (reading)	Heterogeneous study designs
Regan et al. (2021)	Case study	Urban middle school	Adaptive tech + CBM	↑ engagement, ↓ anxiety	Not generalizable
Nelson et al. (2023)	Systematic review	K–8, dyscalculia	Targeted numeracy interventions	Positive effects (math)	Limited longitudinal data
Berninger & Wolf (2018)	Practitioner reference text	Grades 2–4, dysgraphia	Explicit handwriting + CBM monitoring	↑ written output (gains documented)	Short intervention window
Powell et al. (2021)	Mixed methods	Tier 2–3 LD students	AIMSweb + teacher coaching	IEP goal attainment ↑	Urban district bias

Table 2 Summary of Effect Sizes by Academic Domain and Intervention Type

Academic Domain	Intervention Type	Effect Size (Cohen's d)	Source
Reading Fluency	CBM-informed RTI	g = 0.37 (Filderman et al., 2018 meta-analysis)	Fuchs et al., 2012
Reading Comprehension	Data-driven differentiation	Moderate, moderated by baseline	Wanzek et al., 2017
Written Expression	Explicit instruction + CBM	Practitioner text; see source	Berninger & Wolf, 2018
Mathematics (general)	MTSS Tier 2 interventions	Gains documented (no single ES)	Stecker et al., 2008
Mathematics (dyscalculia)	Targeted numeracy programs	Review; varied by study	Nelson et al., 2023
IEP Goal Attainment	AIMSweb + coaching	Not reported (↑ sig.)	Powell et al., 2021
Student Engagement	Adaptive technology + CBM	Qualitative ↑	Regan et al., 2021

➢ *Student Engagement and Participation*

In addition to learning skills acquired, the literature reviewed shows that another secondary benefit of DDI is in relation to student engagement. A qualitative exploration of an urban middle school (Regan et al., 2021) revealed that when students were able to visualize their progress data plotted on a chart against their IEP goals, students reported feeling more 'Owning' their learning, which the authors called 'data transparency as motivation. Students reported increased awareness of being less a "handicapped" and more concerned with incremental skill development, which had significant implications for persistence and school identity.

Theoretically all these findings are coherent. The theory of self-determination (Deci & Ryan, 2000) also suggests that when learners have autonomy, the feeling of competence, and a sense of relatedness, they are more intrinsically motivated, and it is these three that can be supported by careful implementation of data transparency. If students know what they are aiming for, and they can see their own improvement, their level of competence increases. Systematic use of data-driven instruction can ensure tasks that are appropriate for the student's level of engagement, in a way that traditional instruction often cannot keep students with LD engaged.

➢ *Successful Early Identification and Intervention*

One of the most practically important benefits of DDI is that it has the ability to detect learning problems earlier and more reliably than standard assessment schedules. Petscher et al. (2020) showed that systematic universal screening (SUPS) at kindergarten entry and progress monitoring during the first semester demonstrated substantially higher sensitivity for detecting students at risk for reading disability compared to teacher referral alone. The difference is huge: Children identified in kindergarten and targeted intervention before the end of first grade have vastly superior long-term reading outcomes than those identified after second grade.

The RTI model institutionalizes early identification as a structural requirement rather than a judgment made at the teacher's discretion. In RTI there is a systematic net that is catching struggling learners in all grade levels three times a year, before these issues have become cumulative deficits. This proactive approach is one of the most unique aspects of DDI as compared to more traditional "wait to fail" special education practices.

➢ *Teacher Practice and Instructional Responsiveness*

DDI is not just about students' experience, it is about how teachers do their job. Research on the teacher's use of data in high-performing DDI schools always reveals changes in how teachers make instructional decisions: They increasingly look at student data more often; they adjust groupings based on student performance trends; and they plan lessons more intensely according to student data. In districts with AIMSweb coaching, teachers reported greater instructional confidence and greater professional agency, which has implications for teacher retention in special education where teacher turnover is high and chronic.

Critically, the changes in teachers' practices are not sustainable. The literature is unanimous in finding that continuing professional growth, administrative support and dedicated time to review data collaboratively are critical factors for implementing the DDI. Schools that offer these supports realize significantly greater results than those that implement assessment systems without teacher capacity development, with implications for district planning.

- *Barriers to Implementation*

Although it is proven to be effective, there are many reasons that DDI is not implemented widely and properly. What is often mentioned is time, as having teachers available to monitor progress and provide feedback on the data is essential for effective progress monitoring, data review, and instructional adjustment, which is not scheduled in current school practices. The installation of structured data systems in schools with high special education teacher workloads and expectations that they manage compliance documentation may be additive instead of integrative.

The second is training. The skills needed for administration and interpretation of CBMs are very difficult for most pre-service teacher preparation programs to develop systematically. The results of numerous surveys conducted with teachers in special education have shown low confidence with respect to interpretation of data, even among teachers with training in progress monitoring tools (Stecker et al., 2008). A lack of fidelity in the implementation of DDI systems often results in not achieving the predicted outcomes, a phenomenon called "intervention dilution" that makes it more difficult to interpret field level outcomes.

The assessment platforms, adaptive technology, and coaching infrastructure that a mature DDI system needs are scarce in the resource-limited environment of low-income and rural districts. States and districts allocate federal funding under IDEA Part B and ESSA Title I to these investments, but the allocations are quite different.

VI. COMPARATIVE ANALYSIS: DDI VS. TRADITIONAL INSTRUCTION

The comparison of the magnitude of outcomes of data-driven instruction and traditional instructional models is not only about the magnitude of the outcomes, but also about the structural logic. Traditional teaching pays more attention to teaching content, and is assessed by final performance, with a long feedback cycle, weak feedback mechanism, and only relying on the ability and sense of individual teachers to meet student needs. By contrast, Data-driven instruction integrates a characteristic of responsiveness as a system feature: Assessment is ongoing and explicit; decisions are based on performance evidence, not merely teacher judgment; and adjustments take place in response to performance evidence rather than teacher judgment alone.

Table 3 Comparative Analysis: Data-Driven Instruction vs. Traditional Instruction Across Key Dimensions

Dimension	Data-Driven Instruction	Traditional Instruction
Assessment frequency	Ongoing (weekly/biweekly)	Summative (unit/semester)
Instructional grouping	Flexible, performance-based	Fixed or whole-class
IEP alignment	Integrated into daily planning	Periodic, often siloed
Response to learning gaps	Immediate, evidence-based	Delayed or uniform
Teacher decision-making	Data-informed, iterative	Intuition or curriculum-paced
Equity considerations	Explicit in design	Often implicit or absent
Technology use	Adaptive platforms, dashboards	Limited or supplementary
Scalability	Structured via MTSS tiers	Depends on individual teachers

Table 3 shows that the differences between the two models are not only technical; they reveal different views on what school systems are responsible for doing for individual learners. Traditional teaching tacitly presupposes that student variation will converge on a set point on a trajectory, while in DDI, student variation is assumed to be the norm and the design of educational systems must be learning-oriented to actively reflect, embrace and support it. This is a philosophical difference that is the difference between an education that works and one that doesn't for students with learning disabilities, because for a student with learning disabilities, by definition, his or her neurology is not the norm.

Note that DDI is not a complete substitution for all aspects of conventional teaching. The foundation of effective learning environments continues to be content knowledge, effective pedagogy, and positive teacher-student relationships. What DDI brings is a systematic set of processes and procedures to ensure these ingredients are integrated and used correctly – the right students, the right support, the right time – and not just because of the sequence in which it is ordered rather than a data-driven process.

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VII. IMPLICATIONS FOR POLICY AND PRACTICE

The conclusions of this review have implications across all levels of the educational system, from the individual classroom to federal policy and they consistently suggest a need for structural investment in DDI as an institutional practice, not an individual teacher's initiative.

The federal requirement for free and appropriate public education in the least restrictive environment is best met in a DDI system. The law calls for measurable goals, reporting progress, and using evidence to inform selection of interventions; these are all aspects of the RTI/MTSS architecture that DDI systems use. However, implementation of IDEA is very different by state and district, and may be influenced by resource differences. Federal policy should support mechanisms for accountability of DDI aligned practices, such as infrastructure for progress monitoring and professional development with IDEA Part B funds.

The biggest investment at the district level is in teacher preparation and continuous coaching. Structured training in CBM administration and interpretation, data-based instructional decision making, and IEP alignment should be part of the foundation of pre-service teacher education programs, especially those leading to special education licensure, and not optional extras. In-service professional development should incorporate collaborative data review processes (weekly or biweekly data team meetings) that become woven into the fabric of school culture and are not a special assessment exercise for DDI to complete.

The most significant change on the classroom level is an orientation, from being a teacher of the curriculum to being a teacher of the student. DDI encourages teachers to focus on assessment as a tool that provides feedback, not a tool for judging. If this orientation can be genuinely embraced, DDI is not a burden, but a method to tell teachers in very direct and timely language, whether what they are teaching works and who is benefiting from it.

The equity aspects of implementing DDI need to be made explicit. Districts with high percentages of students from historically marginalized communities and high levels of resources challenges and/or potentially problematic assessment bias will need more focused assistance to implement DDI that actually decreases rather than inadvertently increases existing achievement gaps. This encompasses investment in culturally responsive screening instruments, multilingual progress monitoring instruments, and community engagement frameworks that make sure that families of students with LD understand and can meaningfully engage in data-informed IEP process.

VIII. CONCLUSION

The evidence reviewed in this paper supports a clear and consequential conclusion: data-driven instruction, implemented within the RTI and MTSS frameworks and integrated with the legal and pedagogical obligations of the IEP, represents the most robust, scalable, and equitable approach currently available for improving academic outcomes among students with learning disabilities in U.S. K–12 schools. Across reading, writing, and mathematics domains, DDI produces meaningful academic gains, gains that are not attributable to assessment reactivity but reflect genuine skill acquisition, as evidenced by transfer to standardized measures and self-report improvements in engagement and academic identity.

These findings do not suggest that DDI is a panacea, or that its implementation is without challenge. The barriers are real: insufficient teacher preparation, inadequate time for data review, inequitable access to assessment technology, and the persistent structural inequities that shape which students receive high-quality special education services and which do not. Acknowledging these barriers is not an argument against DDI but an argument for the kind of sustained, equity-centered institutional investment that the approach requires to realize its full potential.

What the evidence does establish, compellingly and across multiple study designs, is that the alternative, continuing to deliver uniform instruction to students whose learning profiles are anything but uniform, carries costs that are both educationally and morally untenable. Students with learning disabilities are not failing because their disabilities are intractable. They are failing because educational systems have not yet built the instructional infrastructure that their neurological profiles require. Data-driven instruction is that infrastructure. The imperative now is to build it, equitably and at scale, in every U.S. school.

Future research should prioritize longitudinal studies that track the post-secondary outcomes of students who received high-fidelity DDI across their K–12 experience; multi-site investigations that examine implementation quality across diverse school contexts; and methodologically rigorous evaluations of technology-enabled DDI tools that include equity impact assessments alongside academic outcome data. The field has sufficient evidence to act with confidence. What it needs next is the political will and institutional commitment to do so.

FUTURE RESEARCH DIRECTIONS

This review raises a number of priorities for future enquiry. First, longitudinal studies tracking students with LD from middle school through high school and into post-secondary settings (college, work, and self-support) would significantly bolster support for early DDI investments because they would provide evidence of the long-term outcomes of the investment. Secondly, it is critical to conduct multi-site research to determine if the documented effect sizes reported in the literature hold in schools with high linguistic diversity and staffing shortages and in under-resourced urban schools.

Third, the potential and the current relationship between AI and DDI are worthy of special study. A suite of AI tools designed to monitor students' skills in reading, writing, and mathematics is beginning to emerge, with limited evidence of effectiveness and limited understanding of the impact of the tools on equity.A variety of AI-driven progress monitoring systems are seeing their debut, ranging from tools that analyze student writing samples for syntactic complexity to platforms that generate individual sets of math problems using adaptive algorithms, and reading comprehension tools that leverage natural language processing to provide real-time feedback to students. Tools require critical and independent assessments, beyond efficacy, that account for algorithmic fairness in student subgroups in the field.

Finally, there would be a much better understanding of how data-use mechanisms (data use practices, teacher behaviors, and institutional structures) contribute to observed data use gains, which would greatly enhance the field's ability to develop data use supports. What teachers actually do differently when DDI is successful and why it can be sustained is the knowledge base that is needed for scalable systems change.

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