



# DATA-DRIVEN DECISION MAKING IN K–12 EDUCATION: A REVIEW OF ASSESSMENT TOOLS AND INSTRUCTIONAL INTERVENTIONS

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## ABSTRACT

*This study explores Data-Driven Decision Making (DDDM) in K–12 U.S. public schools. It emphasizes the effectiveness of assessment tools, how data is used to influence interventions, and the obstacles to implementing such decisions. The research combines findings from case studies, empirical research, and organizational reports through a qualitative literature review. Thematic analysis shows that when formative and diagnostic assessments are supported by simple technology, it provides timely insights that guide interventions like personalized learning and curriculum changes. However, broad implementation faces challenges such as limited teacher training, data overload, and resistance to change. The study underscores the importance of professional development, simplified data systems, and strong leadership in enhancing DDDM's impact. It offers recommendations for improving data practices and advocates for further research in rural and non-academic educational settings to promote equity and efficiency.*

**KEYWORDS:** *Data-Driven Decision Making, DDDM, assessment tools, instructional interventions, K-12 public schools.*

## 1.0 INTRODUCTION

In a time when U.S. public schools face growing demands to meet diverse student needs amidst limited resources, the call for evidence-based methods is at an all-time high. Data-Driven Decision Making (DDDM) in K–12 education addresses this demand by utilizing information, such as data on student performance and attendance, to inform decisions regarding teaching, learning, and the distribution of resources (Hamilton et al., 2009). Central to DDDM are assessment tools, which encompass techniques or instruments such as standardized tests, formative quizzes, attendance tracking, or software systems that collect data on student achievement, engagement, or areas that require improvement (Black & Wiliam, 1998). These tools provide the crucial information needed to identify where students require extra assistance.

Instructional interventions are also of great importance, comprising targeted teaching methods or programs such as tutoring, individualized learning plans, or curriculum modifications designed to address the educational needs of both teaching and learning. DDDM is essential in U.S. public schools, where diverse student populations and constrained resources demand precise, evidence-informed strategies to promote effective teaching and address educational inequalities (Wayman et al., 2012). Even with the promise that Data-Driven Decision Making (DDDM) holds for improving educational outcomes, the degree of its implementation, its impact, and the obstacles that impede its application in K–12 public schools in the U.S. remain uncertain, especially regarding current assessment tools and instructional methods. Recent research on DDDM in U.S. K–12 education is sparse, with few studies offering thorough insights into its practical use since 2015 (Schildkamp et al., 2019). This deficiency makes it challenging to comprehend the workings of DDDM and how it can be enhanced to tackle issues like equity and resource management.

This paper seeks to investigate the nature of Data-Driven Decision Making (DDDM) in K–12 U.S. public schools by addressing three pivotal questions. First, which types and examples of assessment tools most effectively collect accurate data on student performance in K–12 education? Second, to what extent do U.S. public schools successfully use data from these assessment tools to guide informed decisions about teaching and learning? Finally, what are the



main barriers to establishing an effective DDDM system in U.S. public schools, and how can these challenges be overcome?

The scope of this study focuses on K–12 U.S. public schools only. Such an analysis would guide educators and policymakers in altering data-driven practices to improve teaching and learning, potentially leading to better student performance, increased engagement, and reduced achievement gaps. (Slavin et al., 2019).

## 2.0 METHODOLOGY

The methodology involves a systematic review of existing studies, case studies, and empirical data on DDDM, assessment tools, and instructional interventions, drawing from academic databases like ERIC, Google Scholar, and reports from educational organizations. This approach ensures a comprehensive analysis of DDDM in U.S. public schools.

### 2.1 Research Design

The study employed a qualitative literature review approach to investigate DDDM practices in K–12 U.S. public schools. A literature review was selected as the primary method as it allowed for the consolidation of evidence to address the research questions comprehensively. The qualitative approach was also chosen for its ability to capture nuanced details about how schools use assessment tools and interventions, as well as the barriers they face, which quantitative methods might overlook (Creswell & Poth, 2018).

This method merged information from case studies, empirical studies, and educational reports to provide in-depth insights into the context, effectiveness, and challenges of DDDM. By examining a diverse range of sources, the study explored real-world applications and examples such as specific school districts using DDDM, which enabled the study to bridge theoretical insights with practical applications, offering a clearer picture of how DDDM functions in U.S. public schools.

### 2.2 Data Sources and Collection

Data collection began with systematic searches in ERIC and Google Scholar, supplemented by targeted queries on Renaissance and HMH using targeted keywords: “data-driven decision-making K–12 U.S.,” “assessment tools education,” and “instructional interventions DDDM.”

These sources were selected based on their relevance to K–12 U.S. public schools and their focus on either DDDM, assessment tools, or instructional interventions. Only sources that provided detailed insights into tool effectiveness, data use in decision-making, or implementation challenges were included to ensure they aligned with the research questions.

The types of data sources analyzed include:

1. Case Studies: These provided detailed accounts of DDDM implementation in specific schools or districts.
2. Empirical Studies: Quantitative and qualitative studies evaluating the impact of formative assessments and data-driven tutoring.
3. Reports: Practical guides and evaluations from organizations like Renaissance and Houghton Mifflin Harcourt.

To ground the study into practice, specific examples were included:

1. Chicago Public Schools (CPS)
2. Long Beach Unified School District (LBUSD)
3. Florida’s Broward County Public Schools.

### 2.3 Inclusion and Exclusion Criteria

Sources were included if they:

- Focused on K–12 U.S. public schools.
- Addressed DDDM, assessment tools, or instructional interventions.

Sources were excluded if they:

- Focused on non-U.S. contexts.



- Focused on higher education.

This selection process ensured a focused dataset relevant to the research questions.

#### 2.4 Data Analysis

The data were analyzed using thematic analysis, a qualitative method that identified patterns and themes across sources (Braun & Clarke, 2006). Themes were organized around the three research questions: effectiveness of assessment tools, extent of data use in decision-making, implementation challenges, and solutions to ensure a structured analysis.

#### 2.5 Theoretical Framework

This research is based on Organizational Learning Theory (OLT), which asserts that organizations, including schools, can enhance their performance by collectively gathering, interpreting, and utilizing knowledge derived from data and experiences. OLT indicates that learning takes place through feedback loops whereby data informs actions, resulting in improved practices and better outcomes. With data-driven decision-making (DDDM), OLT is pertinent as it conceptualizes schools as learning organizations that leverage assessment data to modify teaching strategies and respond to student needs, evident in practices like data-driven interventions. The theory's focus on collaborative learning and adaptation corresponds with how schools apply data-driven decision-making to tackle issues such as limited resources and varied student demographics, offering insights into how data utilization can improve decision-making and organizational efficiency in K–12 education.

Evidence-Based Decision-Making Theory (EBDM) suggests that decisions made in educational settings should be based on empirical evidence to ensure their effectiveness and accountability. It highlights the structured use of data, including student performance indicators, to guide choices regarding curriculum, teaching methods, and resource distribution, emphasizing evidence over instinct or tradition. Evidence-Based Decision-Making Theory is pertinent to this research as it corresponds with the fundamental idea of Data-Driven Decision-Making (DDDM), which focuses on utilizing assessment data to inform instructional interventions. The theory buttresses the study's emphasis on how schools leverage data to meet student needs and tackle issues such as data overload, offering a framework to investigate how evidence-based strategies improve decision-making in K–12 U.S. public schools.

### 3.0 KEY FINDINGS FROM EXISTING LITERATURE

Data-Driven Decision Making (DDDM) employs various data types, including student test results, attendance figures, and behavioral records, to shape decisions about teaching, learning, and school management (Schildkamp et al., 2013). It originated from accountability laws such as the No Child Left Behind Act (2001) and Every Student Succeeds Act (2015) and has become essential to educational reform, urging schools to make decisions based on solid evidence rather than intuition (Kaufman et al., 2014). Moreover, research indicates that DDDM encompasses more than just test scores. It incorporates a wide range of data sources, including classroom observations and demographic information (Mandinach & Schildkamp, 2021).

The body of literature regarding DDDM in K–12 education has expanded since the early 2000s, influenced by accountability measures and the growth of technology, although it remains less developed compared to sectors like business (Kaufman et al., 2014). Prominent journals like *Educational Researcher* and *Teachers College Record*, along with researchers like Kim Schildkamp and Ellen Mandinach, largely shape the field, concentrating on policy-driven applications and classroom practices (Mandinach & Schildkamp, 2021). Recent publications from organizations like Panorama Education and Houghton Mifflin Harcourt (HMH) further highlight practical implementations, stressing the importance of DDDM in promoting equity and efficiency.

Assessment tools are fundamental to DDDM, providing the necessary data to influence educational decisions. These tools encompass standardized tests, which deliver wider insights but may lack immediacy (Black & Wiliam, 1998); formative assessments, such as quizzes or immediate feedback from platforms like Google Classroom, which facilitate continuous monitoring (Dunn et al., 2014); and diagnostic assessments, such as Dynamic Indicators of Basic Early Literacy Skills (DIBELS), which identify specific learning deficiencies (Arundel, 2025). Additionally, technology-based tools and data dashboards (e.g., Northwest Evaluation Association's Measures of Academic Progress, NWEA MAP) have arisen as effective methods for gathering and organizing data, improving accessibility for educators (CRUZ, 2024).



Schildkamp & Poortman (2015) emphasize that the success of assessment tools relies on their timeliness, accessibility, and coherence with instructional objectives. For example, formative and diagnostic tools generally offer more actionable insights than standardized assessments, allowing teachers to react quickly to students' needs. However, research highlights difficulties in their implementation, indicating that merely 6% of teachers have received formal training in DDDM, which limits their capacity to interpret data accurately (Kaufman et al., 2014). Additionally, an overemphasis on test scores can distort priorities, overlooking wider student needs such as engagement or socio-emotional development (Mandinach & Schildkamp, 2021). As a result, the literature advocates for improved professional development to facilitate effective utilization of assessment tools within DDDM (Dunn et al., 2014).

Equally important to DDDM are instructional interventions, which convert assessment data into proposals that can address student requirements. These proposals include personalized learning, where platforms like i-Ready customize content for individual students; differentiated instruction, which modifies teaching approaches based on data; focused tutoring for students facing difficulties; and curriculum modifications to align with identified patterns (Schildkamp & Poortman, 2015).

By building upon assessment data, instructional interventions can greatly improve student outcomes when applied successfully. For instance, research has shown that schools leveraging data-informed interventions experienced significant gains in standardized test scores, particularly with the support of teacher training (van Geel et al., 2016). Additionally, collaborative data teams enhance interventions by encouraging shared decision-making, allowing educators to collectively refine policies (Schildkamp & Poortman, 2015).

Nevertheless, challenges such as data misinterpretation and limited teacher capacity often impede success, as many educators find it difficult to translate data into practical interventions. Therefore, the literature underscores the necessity for continuous support to close this gap.

Beyond the classroom, Data-Driven Decision Making (DDDM) influences decisions at both the school and policy levels, thereby increasing its effectiveness. For instance, schools analyze data to distribute resources, such as funding additional personnel in areas of high need, or to develop professional development programs that are specifically designed to meet teachers' needs (Schildkamp et al., 2013). At the district level, DDDM plays a pivotal role in shaping policies like funding priorities and curriculum standards to tackle systemic issues (DeFlitch, 2024). Efforts to collaborate using data teams are essential for these implementations, allowing schools to align data utilization with larger objectives (Schildkamp & Poortman, 2015).

In conclusion, the research highlights the transformative potential of DDDM in K–12 education.

#### 4.0 DISCUSSION FROM KEY FINDINGS

Through thematic analysis, the study's findings provide comprehensive explanations for the three research questions.

##### 4.1 Effectiveness of Assessment Tools

Thematic analysis indicated that formative assessments, like real-time quizzes and Google Classroom analytics, proved highly effective due to their immediacy and alignment with classroom demands. These tools offered actionable information, allowing teachers to modify their instructions quickly (Dunn et al., 2014; DeFlitch, 2024). Diagnostic tools, such as DIBELS, were particularly useful in pinpointing specific skill gaps and providing precise data for interventions (Amplify 2022). Standardized assessments, including NWEA MAP, offered accurate, wide-ranging data but were less actionable because of the delayed results (Moeller et al, 2018). Technology-driven tools, such as Canvas analytics, improved usability by automating data gathering, although their effectiveness relied on the teachers' familiarity with the system. In Chicago Public Schools, NWEA MAP assessments were utilized to identify deficiencies in math skills across grade levels, facilitating targeted interventions (Moeller et al, 2018). Broward County Public Schools used DIBELS to detect reading gaps, which guided small-group instruction (Arundel, 2022). Long Beach Unified School District capitalized on Google Classroom analytics for weekly monitoring of student progress, which enabled teachers to adapt lessons in real-time (DeFlitch, 2024). These instances highlighted the importance of timeliness and usability of tools to align with instructional interventions. Concerning timeliness, the analysis supports that formative assessments, such as Google Classroom analytics, provided immediate data, allowing Long Beach Unified School District to modify instruction weekly, thereby increasing student engagement (DeFlitch, 2024). Regarding usability, evidence suggests that technology tools like Canvas analytics facilitated automated data collection but required educator training to enhance effectiveness, as the use of such tools depended on intuitive design and teacher preparedness (Dunn et al., 2014). In terms of instructional alignment, findings reveal that diagnostic tools



like DIBELS, employed in Broward County Public Schools to tackle reading gaps, ensured the relevance of data to teaching goals, thereby improving outcomes, while standardized assessments like NWEA MAP, used in Chicago Public Schools were less aligned due to delayed results (Arundel, 2025; Moeller et al, 2018).

#### 4.2 Use of Data in Teaching and Learning Decisions

The analysis indicated that public schools in the U.S. exhibited varying degrees of success in leveraging assessment data to inform teaching decisions. Urban districts, such as Chicago and Long Beach, demonstrated effective utilization of data through tutoring and curriculum modifications, often aided by data teams (Moeller et al, 2018; DeFlitch, 2024). Suburban schools experienced similar success but typically faced fewer resource limitations. Conversely, smaller or rural schools often encountered difficulties due to constrained infrastructure, leading to inconsistent use of data (Schildkamp et al., 2019). Long Beach Unified School District leveraged formative assessment data from Google Classroom to adapt curricula for English Language Learners, resulting in enhanced engagement (DeFlitch, 2024). In Florida's Broward County, i-Ready diagnostic data informed personalized learning plans, resulting in improved reading scores (Broward County Public Schools, 2018). Chicago Public Schools implemented small-group math tutoring based on NWEA MAP data, which led to measurable improvements in student performance (Moeller et al, 2018). These examples illustrate successful data-driven decision-making in well-supported settings. Key themes that emerged include the specificity of interventions and the impact on outcomes. In terms of intervention specificity, the results demonstrate that targeted policies, such as curriculum adjustments based on Google Classroom data for English Language Learners in Long Beach and personalized learning plans using i-Ready in Broward County, proved very effective, significantly improving engagement and reading scores (DeFlitch, 2024; Broward County Public Schools, 2018). Concerning the impact on outcomes, the evidence emphasizes that data-driven decisions led to measurable gains in well-resourced urban areas, whereas rural schools faced limitations due to inadequate infrastructure, reducing their effectiveness (Schildkamp et al., 2019).

#### 4.3 Barriers and Solutions to Effective DDDM

Common barriers included inadequate teacher training, excessive data, and resistance to change. Just 6% of educators received formal training in Data-Driven Decision Making (DDDM), which led to data misinterpretation (Kaufman et al., 2014). Data overload caused challenges for educators, especially in schools utilizing various assessment tools (CRUZ, 2024). In under-resourced schools, teachers often viewed DDDM as an extra burden, leading to widespread resistance to change (Schildkamp et al., 2019). Suggested solutions included enhanced professional development, simpler data systems, and support from leadership. Targeted training initiatives increased data literacy, as demonstrated by workshops on NWEA MAP interpretation in a Texas district (Brown & Adato, 2020). Effective leadership, exemplified by data-driven initiatives in Chicago, helped to foster acceptance and reduce resistance (Moeller et al., 2018). A Texas district adopted professional development to improve teachers' use of NWEA MAP data, leading to more effective interventions (Brown & Adato, 2020). A California school employed a simplified dashboard to effectively manage data from various tools, which increased efficiency (DeFlitch, 2024). Leadership-led data teams in Chicago Public Schools diminished teacher resistance by incorporating DDDM into regular practices (Moeller et al., 2018). Key themes include teacher capacity, systemic support, and shifts in culture. Regarding teacher capacity, evidence suggests that limited training, where only 6% of educators received formal DDDM instruction, resulted in data misinterpretation in under-resourced schools, while targeted professional development in a Texas district improved the usage of NWEA MAP data, thereby enhancing intervention effectiveness (Kaufman et al., 2014). Concerning systemic support, analysis indicates that excessive data posed challenges for educators, yet simple dashboards in a California school improved efficiency by using critical metrics (DeFlitch, 2024). In terms of cultural shifts, findings illustrate that resistance to change was common in under-resourced environments. People find it difficult to accept things they do not fully understand.

#### 4.4 Synthesis of Findings

The thematic analysis from this study disclosed a complex relationship between the effectiveness of assessment tools, the utilization of data for instructional interventions, and the challenges to effective DDDM within K–12 public schools in the U.S. It highlighted their interlinked effects on educational outcomes. Assessment tools such as DIBELS and Google Classroom analytics offered timely and precise data, empowering educators to make informed decisions, as exemplified by Broward County's use of DIBELS to pinpoint reading deficiencies for targeted small-group instruction and Long Beach Unified School District's adaptive curriculum changes for English Language Learners utilizing Google Classroom analytics, both leading to enhanced student engagement and achievement (DeFlitch, 2024). Likewise, Chicago Public Schools harnessed the extensive data from NWEA MAP to provide small-group



math tutoring, resulting in notable academic improvements, illustrating how actionable data can drive instructional interventions (Moeller et al., 2018). Nonetheless, challenges such as insufficient teacher training, with only 6% of educators receiving formal DDDM training, and data overload due to multiple tools, particularly within under-resourced schools, often hinder both the application of tools and the success of interventions (Kaufman et al., 2014; CRUZ, 2024). For example, rural schools faced difficulties with inconsistent data utilization due to limited infrastructure, in contrast to urban districts that had strong data teams (Schildkamp et al., 2019). Approaches like professional development, as seen in a Texas district that enhanced NWEA MAP data interpretation. These findings advance existing literature by focusing on recent applications of tools and specific barriers, emphasizing the necessity for systemic solutions like targeted training and user-friendly data systems to fully tap into the potential of DDDM.

#### 4.5 Implications for DDDM

The findings highlight the critical role of accessible, user-friendly assessment tools and strong teacher support in effective DDDM. Schools that have established strong data systems and provided training, such as those in Long Beach and Chicago, showed better student results, indicating that this approach could be replicated by other schools. Future research should explore DDDM in rural contexts and non-academic outcomes to address current gaps.

### 5.0 LIMITATIONS AND RECOMMENDATIONS

This research examined Data-Driven Decision Making (DDDM) in K–12 public schools across the U.S. through a qualitative review of literature. It is centered on assessment tools, instructional strategies, and challenges in implementation. This chapter presents suggestions to improve the effectiveness of DDDM and the limitations encountered during the research process.

#### 5.1 Recommendations

To promote Data-Driven Decision Making (DDDM) in K–12 public schools in the U.S., policymakers must invest in comprehensive training programs for teachers that enhance their data literacy, allowing them to interpret data from assessment tools such as DIBELS and NWEA MAP effectively, as evidenced by the success seen in Chicago Public Schools.

To overcome challenges like insufficient training and data overload, schools should use user-friendly platforms that merge vital student performance data to facilitate data analysis and alleviate teacher stress, thus enhancing decision-making efficiency.

To address the limitations of the present study, particularly its focus on urban-centered case studies, future research should emphasize studies in rural schools.

The analysis also depended on secondary data, which limited the ability to observe DDDM practices directly within schools. Although this method was thorough, it could not capture the specific nuances of real-time implementation.

The lack of a substantive body of recent DDDM literature, especially concerning rural and non-academic outcomes, including social-emotional learning, is limited and it constrained the study's scope (Schildkamp et al., 2019).

Recent trends indicate a growing focus on incorporating social-emotional data and addressing equity to tackle achievement disparities, signaling a transition toward more inclusive DDDM approaches (EdSurge, 2024)

### 6.0 CONCLUSION

In summary, this research revealed that useful assessment methods, including formative quizzes and diagnostic tools, offer valuable data that aid in instructional interventions, like personalized learning. However, challenges like inadequate training and data overload can often impede effectiveness. These results underscore the ability of data-driven decision-making (DDDM) to improve student performance and support equity in public schools across the U.S. by providing educators with accurate information, while also highlighting the necessity for comprehensive training and user-friendly data systems to address implementation obstacles. As schools continue to navigate the challenge of addressing the varied needs of students with limited resources, DDDM remains an essential approach, and future studies should investigate its use in rural settings and areas beyond academics, such as social-emotional learning.



## REFERENCES

1. Black, P., & Wiliam, D. (1998). *Assessment and classroom learning*. *Assessment in Education: Principles, Policy & Practice*, 5(1), 7–74. <https://doi.org/10.1080/0969595980050102>
2. Braun, V., & Clarke, V. (2006). *Using thematic analysis in psychology*. *Qualitative Research in Psychology*, 3(2), 77-101. [10.1191/1478088706qp0630a](https://doi.org/10.1191/1478088706qp0630a).
3. Bryk, A., Gomez, L., Grunow, A., & LeMahieu, P. (2021). *Learning to Improve: Different types of measures are used for different purposes*. Harvard Education Press.
4. Creswell, J. W., & Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches (4th ed.)*. SAGE Publications.
5. Cruz, A. (2024). *Data-driven decision-making in education: Pros and cons*. HMH Blog. Retrieved August 6, 2025, from <https://www.hmhco.com/blog/data-driven-decision-making-in-education>
6. DeFlitch, S. (2024). *A comprehensive guide to data-driven decision-making in education*. Panorama Education Blog. Retrieved August 6, 2025, from <https://www.panoramaed.com/blog/a-comprehensive-guide-to-data-driven-decision-making-in-education>
7. EdSurge. (2024, April 10). *How data drives strategies for improved student outcomes*. <https://www.edsurge.com/news/2024-04-10-how-data-drives-strategies-for-improved-student-outcomes>
8. Mandinach, E., & Jackson, S. (2012). *Transforming Teaching and Learning through Data-Driven Decision-Making (1st ed.)*. Corwin & SAGE Publications. Mandinach, E., & Schildkamp, K. (2021). *Misconceptions about data-based decision making in education: An exploration of the literature*. *Studies in Educational Evaluation*, 69, 100842. <https://doi.org/10.1016/j.stueduc.2020.100842>
9. Moeller, E., Seeskin, A., & Nagaoka, J. (2018). *Practice-driven data: Lessons from Chicago's approach to research, data, and practice in education*. University of Chicago Consortium on School Research.
10. Brown, R., & Adato, M. (2020, August 14). *Data driven decision making in education: Why it's needed and how to use it*. Renaissance. Retrieved August 6, 2025, from [https://www.renaissance.com/2020/08/14/blog-data-driven-decision-making-in-education-why-its-needed-and-how-to-use-it/Schildkamp, K., & Poortman, C. \(2015\). Factors influencing the functioning of data teams. Teachers College Record, 117\(4\), 1–42. <https://doi.org/10.1177/016146811511700403>](https://www.renaissance.com/2020/08/14/blog-data-driven-decision-making-in-education-why-its-needed-and-how-to-use-it/Schildkamp, K., & Poortman, C. (2015). Factors influencing the functioning of data teams. Teachers College Record, 117(4), 1–42. https://doi.org/10.1177/016146811511700403)
11. Schildkamp K.,(2019). *Data-based decision-making for school improvement: Research insights and gaps*. *Educational Research*, 61(3), 257–273. <https://doi.org/10.1080/00131881.2019.1625716>
12. Van Geel, M., Keuning, T., Visscher, A., & Fox, J.-P. (2016). *Assessing the effects of a school-wide data-based decision-making intervention on student achievement growth in primary schools*. *American Educational Research Journal*, 53(2), 360–394. <https://doi.org/10.3102/0002831216637346>
13. Visscher, A. (2021). *On the value of data-based decision making in education: The evidence from six intervention studies*. *Studies in Educational Evaluation*, 69, 100899. <https://doi.org/10.1016/j.stueduc.2020.100899>