

Teacher Data Literacy and Data-Driven Mathematics Instruction in Primary Education

A Systematic Literature Review

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ABSTRACT

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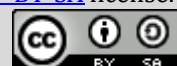
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This study investigates how primary school teachers develop and apply data literacy to support data-driven mathematics instruction in data-rich learning environments. A Systematic Literature Review (SLR) following PRISMA guidelines was conducted, synthesizing 42 peer-reviewed studies published between 2014 and 2025 across major academic databases. The review identifies three key themes. First, teacher data literacy is a multidimensional construct integrating data interpretation, statistical reasoning, and pedagogical decision-making, yet many teachers face challenges in translating data into instructional action. Second, barriers to data use are systemic, including limited training, complex analytics tools, time constraints, and weak institutional support. Third, effective strategies include structured data literacy training, simplified dashboards, collaborative inquiry through Professional Learning Communities (PLCs), and strong instructional leadership. This study integrates Data-Based Decision-Making (DBDM), Technological Pedagogical Content Knowledge (TPACK), and sociocultural perspectives into a unified framework, offering both theoretical insights and practical recommendations for developing sustainable data-driven mathematics teaching practices in primary education.

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Introduction

The rapid integration of digital learning platforms in primary education has transformed the landscape of classroom assessment and instruction by generating unprecedented volumes of student performance data. These data include real-time mastery scores, detailed error patterns, time-on-task metrics, and individualized learning trajectories, all of which offer significant potential to inform pedagogical decision-making. In mathematics education, such data are particularly valuable, as they can reveal fine-grained insights into students' conceptual understanding and misconceptions. When effectively utilized, these insights can support teachers in differentiating instruction, providing targeted feedback, and ultimately improving student learning outcomes. However, despite the growing availability of these data-rich environments, research consistently shows that many teachers struggle to interpret and use learning analytics effectively, leading to underutilization of available tools and missed opportunities for instructional improvement [1], [2]. This persistent gap between data availability and data use underscores the critical importance of teacher data literacy.

Teacher data literacy is broadly defined as the ability to collect, analyze, interpret, and apply student data to inform instructional decisions. It is a multidimensional construct that integrates statistical reasoning, assessment literacy, and pedagogical judgment [3], [4]. In the context of mathematics education, data literacy assumes even greater significance because mathematical thinking often manifests through identifiable patterns of errors and misconceptions. These patterns can be captured through digital responses, automated scoring systems, and learning analytics dashboards, enabling teachers to diagnose learning difficulties with greater precision [5], [6]. Empirical studies indicate that teachers who possess strong data literacy skills are better able to interpret such patterns, adapt their instructional strategies, and enhance student engagement and achievement [7], [8]. Nevertheless, the ability to translate raw data into meaningful pedagogical actions remains a complex and demanding task, particularly for primary school teachers who may have limited training in data analysis.

Despite the recognized importance of data-driven instruction, its implementation remains uneven across primary education contexts worldwide. Several studies attribute this inconsistency to a combination of structural and individual factors, including limited professional development opportunities, inadequate technological infrastructure, and the absence of supportive school cultures that prioritize evidence-based decision-making [9], [10]. Moreover, the effective integration of data into mathematics instruction requires more than technical proficiency. It demands a nuanced understanding of how data relate to student thinking, as well as the ability to engage in collaborative inquiry and reflective practice. In this regard, school-level factors such as leadership support, professional learning communities (PLCs), and shared norms around data use play a crucial role in shaping teachers' engagement

with data [11], [12]. Without these enabling conditions, data-driven practices are unlikely to be sustained, regardless of the availability of technological tools.

While a growing body of research has examined teacher data literacy and learning analytics, these strands of literature have largely developed in parallel, with limited efforts to integrate their insights within the specific context of primary mathematics education. Existing reviews tend to focus on secondary or higher education settings, where data systems and instructional demands differ significantly from those in early-grade classrooms. Consequently, there remains a critical gap in understanding how primary school teachers interpret granular learning data—particularly error patterns associated with early numeracy—and transform these data into actionable instructional strategies. Furthermore, current research often lacks a comprehensive conceptual framework that connects data literacy competencies with pedagogical reasoning and school-level cultural factors. Addressing this gap is essential for advancing both theoretical understanding and practical implementation of data-driven instruction in primary mathematics education.

In response to these challenges, this study employs a Systematic Literature Review (SLR) to synthesize existing research on teacher data literacy, learning analytics, and mathematics instruction in primary schools. The study is guided by the following research question: *How do primary school teachers develop and apply data literacy to support data-driven mathematics instruction?* By systematically analyzing empirical and conceptual studies published over the past decade, this review aims to identify how teachers interpret mathematics learning data, the barriers they encounter, and the strategies and frameworks that support the development of sustainable data-driven teaching practices.

The contribution of this study is twofold. Theoretically, it advances the field by integrating previously fragmented strands of research into a coherent framework that highlights the interplay between data, teacher competencies, and institutional contexts. Practically, it provides evidence-based recommendations for educators, school leaders, and policymakers seeking to strengthen data literacy and promote effective data use in primary mathematics classrooms. Through this dual contribution, the study seeks to support the development of a sustainable data-driven mathematics teaching culture that enhances both teaching quality and student learning outcomes.

Methods

A. Research Design and Review Protocol

This study employed a Systematic Literature Review (SLR) to synthesize existing research on teacher data literacy, learning analytics, and data-driven mathematics instruction in primary education. The review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency, replicability, and

methodological rigor. The SLR approach was selected as it enables the integration of findings from diverse empirical and conceptual studies, thereby providing a comprehensive understanding of how teachers develop and apply data literacy within mathematics instruction contexts.

B. Search Strategy and Data Sources

A systematic search was conducted across five major academic databases: Scopus, Web of Science, ERIC, SpringerLink, and Google Scholar. These databases were selected to ensure broad coverage of high-quality peer-reviewed studies in education, learning analytics, and mathematics pedagogy. The search focused on publications from 2014 to 2025, reflecting the rapid development of digital learning environments and data-driven instructional practices over the past decade.

The search strategy employed combinations of keywords and Boolean operators, including:

- “data-driven instruction”
- “teacher data literacy”
- “learning analytics”
- “primary school” OR “elementary education”
- “mathematics education” OR “numeracy”

C. Study Selection Process

The study selection process followed the PRISMA flow procedure. The initial database search yielded 512 records, of which 86 duplicates were removed, resulting in 426 unique records for screening. Titles and abstracts were then reviewed to assess relevance, leading to the exclusion of studies that did not meet the inclusion criteria. This stage resulted in 97 articles selected for full-text assessment. After applying the inclusion and exclusion criteria, 42 studies were retained for the final synthesis.

D. Inclusion and Exclusion Criteria

To ensure the relevance and quality of the selected studies, the following criteria were applied:

Inclusion Criteria

1. Peer-reviewed journal articles published between 2014 and 2025
2. Studies focusing on data use, teacher data literacy, or learning analytics in primary education
3. Research related to mathematics education or numeracy
4. Empirical, conceptual, or review studies with clear methodological or theoretical contributions

Exclusion Criteria

1. Studies conducted in secondary or tertiary education contexts

2. Articles focusing solely on technological development without pedagogical implications
3. Non-peer-reviewed reports, except for widely recognized institutional publications

E. Quality Assessment

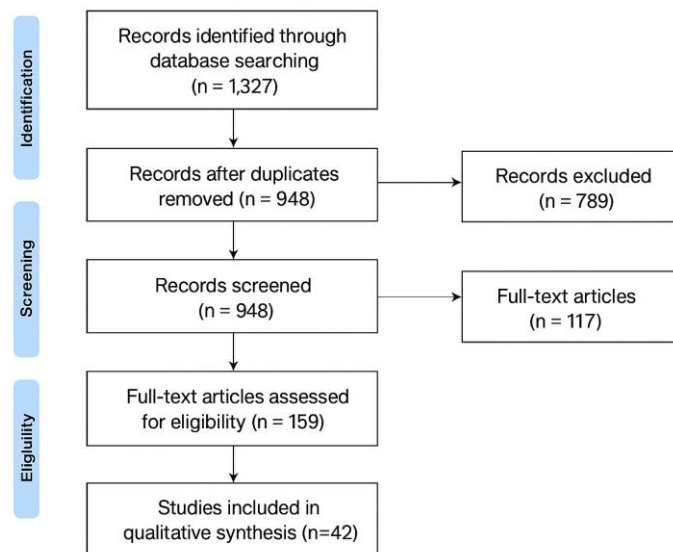
To enhance the methodological rigor of the review, each selected study was evaluated using a structured quality assessment framework. The assessment focused on three key criteria: methodological clarity, data validity, and relevance to the research focus.

Table 1. Quality Assessment Criteria

1. Criteria	2. Description	3. Score
4. Methodological clarity	5. Clarity and appropriateness of research design	6. 1–3
7. Data validity	8. Evidence of reliability and validity of data	9. 1–3
10. Relevance	11. Direct relevance to data literacy and mathematics education	12. 1–3

Each study received a total score ranging from 3 to 9. Only studies scoring ≥ 5 were included in the final synthesis to ensure sufficient quality and relevance. This process helped filter out studies with weak methodological foundations or limited applicability to the research question.

The PRISMA flow diagram illustrates the systematic process of study identification, screening, eligibility assessment, and final inclusion. The exclusion process was guided by predefined criteria to ensure methodological rigor and contextual relevance.



F. Data Analysis Procedure

The selected studies were analyzed using a thematic synthesis approach, which allows for the systematic identification and integration of patterns across studies. A three-stage coding process was employed:

1. Open coding: Initial concepts related to teacher data literacy, learning analytics, and instructional practices were identified and labeled.
2. Axial coding: Related concepts were grouped into broader categories, such as teacher competencies, barriers to data use, and instructional strategies.

3. Selective coding: Core themes were developed by integrating categories into overarching constructs aligned with the research question.

This iterative coding process enabled the development of a structured understanding of how teachers interpret and apply learning data in mathematics instruction.

Table 2. Thematic Coding Process (Open–Axial–Selective Coding)

Open Coding (Initial Concepts)	Axial Coding (Categories)	Selective Coding (Themes)
Difficulty interpreting dashboards	Data interpretation challenges	Teacher Data Literacy Competencies
Limited statistical knowledge	Analytical skill gaps	Teacher Data Literacy Competencies
Misunderstanding error patterns	Diagnostic limitations	Teacher Data Literacy Competencies
Complex dashboard interfaces	Tool usability issues	Barriers to Data Use
Time constraints for analysis	Workload challenges	Barriers to Data Use
Lack of training programs	Professional development gaps	Barriers to Data Use
Weak collaboration among teachers	Lack of PLC structures	Barriers to Data Use
Use of PLC discussions	Collaborative data practices	Strategies for Data-Driven Culture
Instructional differentiation based on data	Data-informed teaching practices	Strategies for Data-Driven Culture
Coaching and mentoring support	Capacity-building strategies	Strategies for Data-Driven Culture
Leadership encouragement	Institutional support	Strategies for Data-Driven Culture

The coding process revealed a progression from fragmented individual challenges (open coding) to structured categories (axial coding), and ultimately to three overarching themes (selective coding): (1) teacher data literacy competencies, (2) barriers to data use, and (3) strategies for building a data-driven teaching culture. This hierarchical coding structure strengthens the analytical rigor of the synthesis and ensures alignment with the research question.

G. Conceptual Framework

To guide the synthesis and interpretation of findings, this study adopts an integrated conceptual framework grounded in three complementary theoretical perspectives. First, Data-Based Decision-Making (DBDM) provides a foundation for understanding how teachers use evidence to inform instructional decisions in an iterative manner. Second, the Technological Pedagogical Content Knowledge (TPACK) framework highlights the integration of technological tools, pedagogical strategies, and subject matter knowledge required for effective teaching. Third, a sociocultural perspective emphasizes the role of collaborative practices, such as Professional Learning Communities (PLCs), in shaping how teachers engage with and interpret data within institutional contexts.

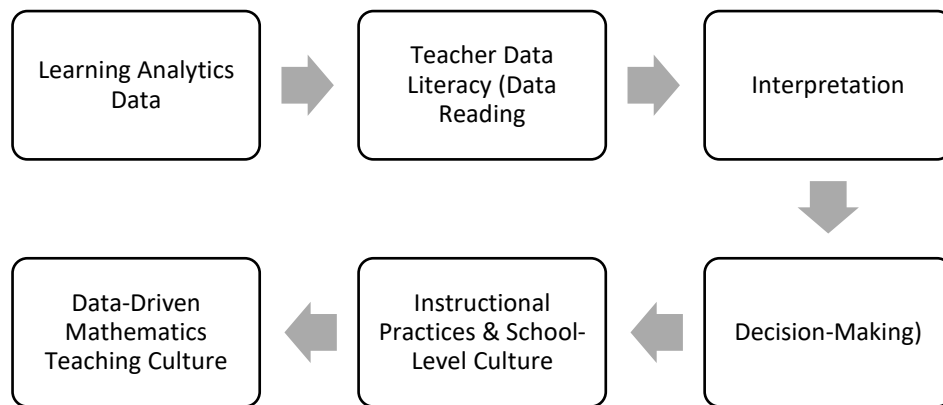


Fig. 1. Conceptual Framework for Developing a Data-Driven Mathematics Teaching Culture

The conceptual framework illustrates the dynamic interaction between data, teacher competencies, and institutional factors. Digital learning platforms generate diverse forms of student performance data, which teachers interpret through data literacy competencies such as error analysis, trend identification, and evidence-based decision-making. These competencies directly inform instructional practices, including differentiation, targeted feedback, and the identification of student misconceptions.

At the same time, school-level conditions—such as leadership support, collaborative inquiry through PLCs, and shared norms regarding data use—shape how teachers collectively engage with data. The interaction between individual competencies and institutional support structures ultimately determines the sustainability of data-driven practices. When these elements are effectively aligned, they contribute to the development of a robust and sustainable data-driven mathematics teaching culture in primary schools.

Results and Discussion

A. Theme 1: Mathematics Learning Data and Teacher Data Literacy Competencies

The synthesis reveals that contemporary digital mathematics platforms generate diverse and granular forms of learning data, including mastery levels, time-on-task metrics, error logs, misconception maps, and dynamic progress dashboards [15], [16]. These data provide significant opportunities for teachers to diagnose student understanding and tailor instruction accordingly. However, across the reviewed studies, a consistent pattern emerges: primary school teachers frequently encounter difficulties in interpreting these data in pedagogically meaningful ways.

While teachers generally recognize the value of learning analytics, their competencies remain uneven, particularly in areas such as statistical reasoning, data visualization, and the translation of data patterns into instructional strategies [17], [18]. This inconsistency reflects

not merely a technical skills gap but a deeper epistemic challenge. Teachers are required to move beyond surface-level interpretation of data (e.g., identifying low scores) toward higher-order reasoning that connects data representations with underlying student thinking and misconceptions [19], [20]. In this sense, data literacy should be conceptualized not as an isolated technical competence but as a form of pedagogical reasoning mediated by data.

This finding aligns with the theoretical foundations of Data-Based Decision-Making (DBDM), which emphasize iterative cycles of data interpretation, instructional adjustment, and evaluation. However, the reviewed studies suggest that many teachers operate at the initial stages of this cycle, with limited progression toward reflective and adaptive practices. From a TPACK perspective, this gap indicates insufficient integration between technological knowledge (understanding dashboards), pedagogical knowledge (instructional strategies), and content knowledge (mathematics concepts).

Furthermore, the findings demonstrate that teachers with stronger data literacy competencies are more likely to implement effective differentiation strategies and provide high-quality, targeted feedback, resulting in improved student learning outcomes [21], [22]. This underscores the importance of developing integrated data literacy training models that explicitly connect data interpretation with mathematics pedagogy. Without such integration, the potential of learning analytics to enhance instructional quality remains underutilized.

To clarify the relationship between different types of mathematics learning data and the competencies required for their effective use, Table 3 synthesizes key data forms alongside corresponding teacher skills and their instructional implications. This mapping highlights how data interpretation must be directly connected to pedagogical decision-making in classroom practice.

Table 3. Types of Mathematics Learning Data, Teacher Competencies, and Instructional Implications

Data Type	Description	Required Competency	Instructional Implication
Error patterns	Repeated student mistakes in mathematical tasks	Diagnostic reasoning	Identifying misconceptions and designing targeted remediation strategies
Mastery scores	Percentage of achieved learning objectives	Data interpretation	Adjusting instruction based on mastery levels and grouping students
Progress data	Trends in student performance over time	Trend analysis	Monitoring learning trajectories and adapting pacing of instruction
Real-time responses	Immediate student answer logs from digital systems	Rapid decision-making	Providing instant feedback and adjusting teaching in real-time
Dashboard visualizations	Graphical summaries (charts, heatmaps, analytics panels)	Data visualization literacy	Translating visual data into actionable teaching strategies

B. Theme 2: Barriers to Implementing Data-Driven Mathematics Teaching

The analysis identifies multiple, interrelated barriers that constrain the effective implementation of data-driven instruction in primary mathematics classrooms. Importantly, these barriers are not isolated but systemic, reflecting the interaction between teacher capacity, technological design, and institutional context.

First, limited professional development in data literacy remains a pervasive issue. Many teachers report receiving only basic training focused on tool operation rather than deeper analytical reasoning or pedagogical application [25], [26]. This results in superficial engagement with data, where teachers may access dashboards but lack the confidence or expertise to interpret them effectively.

Second, the design of learning analytics tools themselves presents significant challenges. Complex dashboards often display excessive or poorly structured information, leading to cognitive overload and reducing usability [27], [28]. From a design perspective, this indicates a misalignment between system functionality and teachers' cognitive and pedagogical needs. In line with TPACK theory, effective data use requires not only access to technology but also the alignment of technological affordances with pedagogical practices.

Third, time constraints emerge as a critical barrier. Teachers frequently report insufficient time to engage in systematic data analysis, particularly in high-demand classroom environments with large student populations [29], [30]. This limits the integration of data use into routine instructional practices, reducing it to an occasional rather than sustained activity.

Fourth, and perhaps most critically, school culture plays a decisive role. In contexts where collaborative inquiry and evidence-based decision-making are not institutionalized, teachers are less likely to engage meaningfully with data [31], [32]. From a sociocultural perspective, data use is not solely an individual practice but a socially mediated activity shaped by shared norms, leadership expectations, and collaborative structures.

Taken together, these findings suggest that the challenges of data-driven instruction cannot be addressed through isolated interventions. Instead, they require a systemic approach that aligns teacher competencies, technological design, and institutional culture. Without such alignment, even well-designed analytics tools are unlikely to produce meaningful instructional change.

The systemic nature of challenges in data-driven instruction is summarized in Table 4, which presents key barriers along with their instructional impacts and broader system-level interpretations. This synthesis demonstrates that obstacles to data use are not merely individual limitations but reflect structural and design-related misalignments.

Table 4. Systemic Barriers to Data-Driven Mathematics Instruction

Barrier	Description	Instructional Impact	System-Level Interpretation
Low data literacy	Difficulty interpreting graphs and analytics	Ineffective or incorrect instructional decisions	Indicates gap in teacher professional preparation
Complex dashboards	Overly dense or unclear data visualization	Cognitive overload and disengagement	Reflects poor alignment between tool design and user needs (TPACK misalignment)
Time limitations	Limited time for data analysis	Infrequent or superficial data use	Structural workload issue requiring institutional support
Lack of training	Minimal professional development in data use	Low confidence and inconsistent practices	Weak capacity-building systems in schools
Weak school culture	Lack of collaborative data inquiry norms	Unsustained or isolated data use	Absence of sociocultural support for data-driven practices

C. Theme 3: Strategies and Frameworks to Build a Data-Driven Teaching Culture

The literature identifies several strategies that support the development of a sustainable data-driven mathematics teaching culture. These include structured data literacy training, simplified and user-centered dashboard design, coaching and mentoring models, collaborative teacher teams, and strong instructional leadership [35], [36].

Among these, Professional Learning Communities (PLCs) emerge as particularly influential. Studies consistently show that when teachers engage in collaborative data discussions, their ability to interpret data and respond instructionally improves significantly [37], [38]. From a sociocultural perspective, PLCs function as mediating structures that transform individual data interpretation into shared pedagogical knowledge. This collective sense-making process enables teachers to move beyond isolated analysis toward coordinated instructional action.

In addition, leadership plays a critical role in sustaining data-driven practices. School leaders who establish clear expectations for data use, allocate dedicated time for data analysis, and model evidence-based decision-making contribute to the institutionalization of data use [39], [40]. This aligns with DBDM principles, where organizational support is essential for sustaining iterative cycles of data-informed improvement.

Another key finding concerns the importance of usability-focused dashboard design. Simplified visualizations and reduced data complexity have been shown to enhance teachers' engagement and reduce cognitive load. This highlights the need for closer collaboration between educational researchers, teachers, and system designers to ensure that analytics tools are pedagogically meaningful and user-friendly.

Despite these promising strategies, the synthesis also reveals important limitations. While PLCs and coaching models are effective, questions remain regarding their scalability and long-term sustainability across diverse educational contexts. Furthermore, most existing studies rely on short-term interventions, with limited evidence on how data literacy develops over time.

Table 5 outlines evidence-based strategies for developing a sustainable data-driven mathematics teaching culture, linking each intervention to its observed outcomes and underlying theoretical foundations. This integrative perspective emphasizes the importance of aligning practice with established educational theories.

Table 5. Strategies for Building a Data-Driven Mathematics Teaching Culture

Strategy	Description	Outcome	Theoretical Link
Data literacy training	Structured workshops on data interpretation and analytics	Improved teacher competence in data use	DBDM (capacity building for evidence-based decisions)
Simplified dashboards	User-friendly visualizations with reduced complexity	Reduced cognitive load and increased usability	TPACK (alignment of technology and pedagogy)
PLC-based data meetings	Collaborative discussions on student data	Shared understanding and collective decision-making	Sociocultural theory (learning through collaboration)
Coaching and mentoring	Individualized support for teachers	Increased confidence and sustained practice	Situated learning (guided practice)
Leadership support	Policies and leadership practices promoting data use	Institutionalization of data-driven culture	DBDM + organizational learning theory

D. Cross-Theme Synthesis and Research Gaps

The cross-study synthesis highlights three overarching insights. First, teacher data literacy is a multidimensional construct that integrates cognitive, pedagogical, and social dimensions. Second, barriers to data use are systemic rather than individual, requiring coordinated interventions across multiple levels. Third, effective strategies emphasize collaborative and sustained engagement with data, rather than one-off training initiatives.

However, significant research gaps remain. The literature is dominated by cross-sectional and case-based studies, with limited use of longitudinal or experimental designs. As a result, there is insufficient evidence on how teacher data literacy evolves over time or how sustained interventions impact instructional practice and student outcomes. Additionally, the scalability of successful models, such as PLC-based data inquiry, remains underexplored.

To provide a higher-level synthesis across the reviewed studies, Table 6 presents a cross-theme analysis that integrates key findings, methodological trends, theoretical insights, and identified research gaps. This synthesis underscores the need for more robust and longitudinal research designs in the field.

Table 6. Cross-Study Analytical Synthesis and Research Gaps

Theme	Key Findings	Dominant Methods	Theoretical Insight	Research Gap
Data Literacy	Teachers struggle with deep interpretation and pedagogical translation	Surveys, interviews	Data literacy is multidimensional (cognitive-pedagogical)	Lack of intervention and experimental studies

Theme	Key Findings	Dominant Methods	Theoretical Insight	Research Gap
Barriers	Challenges are systemic (time, tools, culture)	Case studies	Misalignment between technology, pedagogy, and context (TPACK)	Limited longitudinal evidence
Strategies	PLCs and coaching improve practice	Mixed methods	Learning is socially mediated (sociocultural perspective)	Scalability and sustainability unclear

Implications

A. Theoretical Implications

This study advances the conceptualization of teacher data literacy by framing it as an integrative construct that extends beyond technical skills to include pedagogical reasoning and sociocultural engagement. This perspective bridges gaps between DBDM, TPACK, and sociocultural theory.

B. Practical Implications

Schools should implement structured, practice-oriented data literacy training, redesign analytics dashboards for usability, and institutionalize collaborative data practices through PLCs and coaching systems.

C. Policy Implications

Policymakers should embed data literacy competencies into teacher professional standards and support systemic integration of learning analytics within primary education systems.

Conclusion

This study demonstrates that the effective use of learning analytics in primary mathematics education depends not only on data availability but also on teachers' capacity to interpret and apply data within pedagogically meaningful contexts. Teacher data literacy emerges as a multidimensional construct that integrates cognitive, pedagogical, and sociocultural dimensions, requiring alignment with technological tools and institutional support systems.

The findings further reveal that barriers to data-driven instruction are systemic, highlighting the need for coordinated interventions that address teacher training, tool design, and school culture. Strategies such as structured professional development, user-centered analytics dashboards, collaborative inquiry through Professional Learning Communities (PLCs), and strong leadership support are essential for sustaining data-informed practices.

By integrating DBDM, TPACK, and sociocultural perspectives, this study provides a comprehensive framework for understanding and advancing data-driven mathematics teaching. Future research should prioritize longitudinal and experimental designs to examine

the sustained impact of data literacy development and explore the potential of emerging AI-driven analytics in supporting real-time instructional decision-making.

Conflict of Interest

The authors declare no conflict of interest.

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