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DATA SCIENCE IN BASIC EDUCATION: AN EVIDENCE-BASED FRAMEWORK INTEGRATING LEARNING AND ASSESSMENT

CIÊNCIA DE DADOS NA EDUCAÇÃO BÁSICA: UM FRAMEWORK BASEADO EM EVIDÊNCIAS QUE INTEGRA APRENDIZAGEM E AVALIAÇÃO

CIENCIA DE DATOS EN LA EDUCACIÓN BÁSICA: UN MARCO BASADO EN EVIDENCIAS QUE INTEGRA APRENDIZAJE Y EVALUACIÓN

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ABSTRACT

In an increasingly data-driven society, preparing new generations with robust competencies in science, technology, engineering, arts and mathematics (STEAM) is essential. Within this context, Data Science (DS) education requires the development of foundational mathematical concepts, terminology, and cognitive structures that support students' progression from introductory to advanced levels. learnipedagogical approaches must enable learners not only to understand data but also to creatively and efficiently apply knowledge to tasks such as data collection, preprocessing, analysis, and visualization. This paper identifies persistent gaps in the design and evaluation of DS teaching initiatives in Basic Education and proposes an evidence-based pedagogical framework to address these challenges. Grounded in international literature and cognitive psychology, the framework integrates well-established learning principles, such as distributed practice, retrieval testing, and iterative project-based learning, with formative assessment tools that strengthen retention, transfer, metacognition, and engagement. The analysis demonstrates that the lack of coherent assessment models weakens the institutionalization of DS as a curricular component and limits its pedagogical effectiveness. The proposed framework offers a unified structure that aligns teaching strategies, learning progressions, and assessment instruments, while remaining adaptable to diverse lol contexts. By centering instructional design on scientific evidence, the model supports teachers in implementing practices that are both pedagogically sound and operationally feasible. The study concludes that fostering data literacy in Basic Education through evidence-based teaching is a crucial step toward promoting educational equity, digital citizenship, and students' capacity to navigate and interpret the information-rich environments of the current digital era.

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Keywords: Data Science Education. Formative Assessment. Evidence-Based Learning. Basic Education.

RESUMO

Em uma sociedade cada vez mais orientada por dados, é essencial preparar novas gerações com competências robustas em ciência, tecnologia, engenharia, artes e matemática (STEAM). Nesse contexto, a educação em Ciência de Dados exige o desenvolvimento de conceitos matemáticos fundamentais, terminologia específica e estruturas cognitivas que sustentem a progressão dos estudantes de níveis introdutórios a avançados. As abordagens pedagógicas devem possibilitar que os estudantes não apenas compreendam os dados, mas também apliquem o conhecimento de forma criativa e eficaz em tarefas como coleta, pré-processamento, análise e visualização de dados. Este artigo identifica lacunas persistentes no desenho e na avaliação de iniciativas de ensino de Ciência de Dados na Educação Básica, particularmente o desalinhamento entre estratégias de ensino, progressões de aprendizagem e práticas avaliativas, e propõe um framework pedagógico baseado em evidências para enfrentar esses desafios. O estudo adota uma abordagem qualitativa e exploratória, fundamentada em uma revisão narrativa da literatura e em uma síntese integrativa de pesquisas provenientes da psicologia cognitiva, das ciências da aprendizagem e da avaliação educacional, orientada pela seguinte questão: quais estratégias de ensino e modelos avaliativos podem apoiar de forma eficaz a institucionalização da Ciência de Dados na Educação Básica? Ancorado na literatura internacional, o framework proposto integra princípios consolidados de aprendizagem, como a prática distribuída, a aprendizagem baseada em recuperação e atividades iterativas baseadas em projetos, a instrumentos de avaliação formativa voltados ao fortalecimento da retenção, da transferência do conhecimento, da metacognição e do engajamento dos estudantes. A análise demonstra que a ausência de modelos avaliativos coerentes fragiliza a institucionalização da Ciência de Dados como componente curricular e limita sua efetividade pedagógica. Ao articular sistematicamente estratégias de ensino, progressões de aprendizagem e instrumentos de avaliação formativa, o framework oferece uma estrutura operacional e adaptável para implementação em sala de aula. Sustentado por evidências empíricas reportadas na literatura, o estudo conclui que promover o letramento em dados na Educação Básica por meio de práticas pedagógicas baseadas em evidências é um passo fundamental para o fortalecimento da equidade educacional, da cidadania digital e da capacidade dos estudantes de interpretar e atuar em ambientes contemporâneos ricos em informação.

Palavras-chave: Ciência de Dados na Educação. Avaliação Formativa. Aprendizagem Baseada em Evidências. Educação Básica.

RESUMEN

En una sociedad cada vez más orientada por los datos, es esencial preparar a las nuevas generaciones con competencias sólidas en ciencia, tecnología, ingeniería, artes y matemáticas (STEAM). En este contexto, la educación en Ciencia de Datos (CD) requiere el desarrollo de conceptos matemáticos fundamentales, terminología específica y estructuras cognitivas que sustenten la progresión de los estudiantes desde niveles introductorios hasta avanzados. Los enfoques pedagógicos deben permitir que los estudiantes no solo comprendan los datos, sino que también apliquen el conocimiento de manera creativa y eficaz en tareas como la recolección, el preprocesamiento, el análisis y la visualización de datos. Este artículo identifica brechas persistentes en el diseño y la evaluación de iniciativas de enseñanza de la Ciencia de Datos en la Educación Básica, en particular, la desalineación entre estrategias de enseñanza, progresiones de aprendizaje y prácticas de evaluación, y propone un marco pedagógico basado en evidencias para abordar estos desafíos. El estudio adopta un enfoque cualitativo y exploratorio, fundamentado en una revisión narrativa de la literatura y en una síntesis integradora de investigaciones provenientes de la psicología cognitiva, las ciencias del aprendizaje y la evaluación educativa, guiado por la siguiente pregunta: ¿qué estrategias de enseñanza y modelos de evaluación pueden apoyar eficazmente la institucionalización de la Ciencia de Datos en la Educación Básica? Anclado en la literatura internacional, el marco propuesto integra principios consolidados de aprendizaje, como la práctica distribuida, el aprendizaje basado en la recuperación y actividades iterativas basadas en proyectos, con instrumentos de evaluación formativa orientados al fortalecimiento de la retención, la transferencia del conocimiento, la metacognición y el compromiso de los estudiantes. El análisis demuestra que la ausencia de modelos de evaluación coherentes debilita la institucionalización de la Ciencia de Datos como componente curricular y limita su efectividad pedagógica. Al articular de manera sistemática estrategias de enseñanza, progresiones de aprendizaje e instrumentos de evaluación formativa, el marco ofrece una estructura operativa y adaptable para su implementación en el aula. Sustentado en evidencias empíricas reportadas en la literatura, el estudio concluye que promover la alfabetización en datos en la Educación Básica mediante prácticas pedagógicas basadas en evidencias constituye un paso fundamental para fortalecer la equidad educativa, la ciudadanía digital y la capacidad de los estudiantes para interpretar y actuar en entornos contemporáneos ricos en información.

Palabras clave: Educación en Ciencia de Datos. Evaluación Formativa. Aprendizaje Basado en Evidencias. Educación Básica.

1 INTRODUCTION: THE IMPERATIVE FOR DATA SCIENCE EDUCATION

The rapid adoption of advanced technologies is transforming multiple dimensions of contemporary life. Rather than focusing solely on labor market projections, this transformation raises broader questions about citizens engage with digital systems, algorithms, and data-intense environments. According to the most recent report from the World Economic Forum (2025) on the Future of Work, 86% of the 1,043 companies surveyed, employing more than 14 million workers across various sectors, expect Artificial Intelligence (AI) and information processing technologies, such as big data, to transform their businesses by 2030.7. Although these trends are often framed in economic terms, they also signal the expanding presence of data-driven infrastructures in everyday civic, social, and institutional interactions.

Olari and Romeike (2024) discuss the importance of AI education and emphasize the critical role of data in the development and understanding of these systems. This includes teaching primary and secondary school students how computers learn from data and the importance of statistical inference in identifying patterns. When students understand data as the central element of algorithmic decision-making, they are better prepared not only for professional contexts but also for informed and critical participation in society. By framing data as a central component of AI, students can gain a deeper awareness of how automated systems shape opportunities, rights, and collective life.

At the same time, data literacy should reveal to students the potential risks, such as algorithmic bias, discriminatory results, privacy, and broader ethical dilemmas. Addressing these issues in educational settings is crucial to ensuring that young people not only acquire knowledge about the techniques involved with data but also develop a critical understanding of how biased or incomplete datasets can perpetuate and even exacerbate social disparities.

This trend underscores the need to prepare new generations with competencies in Science, Technology, Engineering, Arts and Mathematics (STEAM), with a particular emphasis on Data Science (DS). At its foundation, DS education focuses on developing skills such as selecting, cleaning, analyzing, visualizing, and interpreting data (Wolff et al., 2016). It also promotes critical thinking, effective communication of evidence-based arguments, and the construction of meaningful narratives grounded in data. In a democratic context increasingly mediated by information flow, these competencies become central to civic agency, decision-making, and equitable participation.

Driven by the increasing importance of data literacy for both social life and educational equity, various international initiatives have sought to integrate DS into school curricula. A prominent example is the initiative DataScience4Everyone, a coalition of policymakers, industry leaders, schools, and scholars committed to promoting data science education (DataScience4Everyone, 2024). Their work has outlined 12 comprehensive curricula for high school education, including programs such as Bootstrap: Data Science (BS:DS), Code.org, CodeHS, CourseKata, Data8, DataCamp, Education Development Center, Key2Stats, STEMcoding, Stats Medic, Introduction to Data Science (IDS), and YouCubed.

Although many of these initiatives were initially motivated by workforce needs, they increasingly emphasize the civic dimension of data literacy, particularly the ability to interpret public information, recognize structural inequalities, and make informed decisions. An inspirational example is the Girl in Data Science Project, directed to middle school girls, mainly afro-descendent students in socioeconomic vulnerable contexts (Firmino et al., 2025). Participants have developed data-informed solutions such as proposals to reduce food waste in school meals and simple games that reveal mobility constraints within their communities, illustrating how data can support collective awareness and local problem-solving.

Despite these advancements, a gap persists: the lack of systematic and evidence-based strategies to assess student learning in these programs. Most studies are limited to describing the curricula, detailing the implementation processes, addressing challenges, and conducting exploratory evaluations of students' impressions and achievements (Adisa et al., 2024; Barany et al., 2024; Gould et al., 2016; Heinemann et al., 2018; Schanzer et al., 2022; Sharma and LePendu, 2022; Walker et al., 2023). Few works integrate pedagogical objectives, teaching strategies, and assessment instruments in cohesive design. This misalignment undermines the scalability and consolidation of DS as a curricular component essential to citizenship in the digital age.

In response to these limitations, this paper proposes a teaching and assessment integrated model for DS learning in basic education. Anchored in evidence from cognitive and educational psychology and formative educational assessment, the model links effective teaching strategies– such as distributed practice, retrieval testing, and self-explanation (Latimier et al., 2021; Oakley et al., 2021) – with evaluative instruments like rubrics, structured feedback, and continuous diagnostics. The approach reframes assessment not as a gatekeeping mechanism but as pedagogical practice that supports student autonomy, reflection, and informed engagement with data. Unlike traditional summative approaches, the proposal positions the teacher as an active mediator of learning.

Evidence-based strategies from these fields, known to enhance learning and retention, could significantly improve DS program design if applied systematically. Learning assessment, when grounded in empirical and cognitive evidence, becomes an essential tool for guiding teaching, supporting students, and offering feedback to educators. Black and Wiliam (1998), Sadler (1989), and Hattie and Timperley (2007) show that assessment strategies centered on feedback, continuous diagnostics, and clarity of criteria promote substantial gains. Because DS requires students to navigate ambiguity, evaluate evidence, and reason ethically, formative assessment is especially crucial for ensuring that these competencies develop in meaningful and equitable ways.

These gaps highlight the need for more comprehensive research into the effectiveness of K-12 DS curricula. Addressing these challenges requires not only developing innovative teaching methodologies but also implementing rigorous evaluation aligned with evidence-based learning principles, particularly those discussed throughout this paper, such as distributed practice, retrieval-based learning, and self-explanation, which have demonstrated strong empirical effects on retention, conceptual understanding, and knowledge transfer. By integrating DS into educational processes aimed at strengthening critical, responsible, and participatory citizenship, schools can help ensure that young people understand and shape the data-driven structures that influence everyday life.

2 LEARNING REVIEW AND FRAMEWORK DEVELOPMENT

This research adopts a qualitative and exploratory approach, grounded in a narrative literature review and an integrative synthesis of theoretical and empirical evidence from cognitive psychology, the learning sciences, and educational assessment. The methodology is oriented towards addressing the central research question: Which teaching strategies and evaluative models can effectively support the institutionalization of Data Science (DS) in Basic Education?

Given the emerging and interdisciplinary nature of DS in education, a qualitative, conceptual approach was adopted to articulate a pedagogical and assessment framework informed by consolidated scientific evidence. This design is particularly appropriate for fields in which empirical studies remain dispersed across domains, and where synthesizing theoretical contributions is essential for guiding future experimental research. The construction of the proposed framework followed three main stages:

1. Review of international and national literature: Survey of publications in databases such as Scopus, Web of Science, and ERIC; Inclusion of studies addressing: (i) teaching data science in school contexts, (ii) evidence-based learning strategies, and (iii) formative assessment and impact evaluation instruments in education; selection

criteria included articles, technical reports, and systematic reviews that offered relevant empirical or theoretical foundations;

2. Analytical synthesis: Organization of evidence into three axes: (i) effective cognitive strategies for knowledge retention and transfer, (ii) formative assessment instruments, and (iii) evaluation methodologies in educational interventions; analytical procedures included identifying convergences, gaps, and opportunities for integrating teaching and assessment approaches;
3. Proposal of the framework: Integration of evidence into an articulated pedagogical model structured around four axes (evidence-based teaching, continuous formative assessment, curricular integration, and equity); formulation of recommendations for the validation of the framework based on prospective research already described in the literature including randomized controlled trials (RCTs), quasi-experiments, and alternative low-cost methodologies.

This is a conceptual and propositional study that depends on the quality and breadth of the reviewed sources. Although the proposal is anchored in consolidated theoretical and empirical foundations, further empirical testing is required to evaluate the effectiveness and scalability of the proposed framework.

3 THEORETICAL FOUNDATIONS: LEARNING SCIENCE AND DATA LITERACY

In recent years, advancements in cognitive science, psychology, and neuroscience have significantly deepened our understanding of how the brain learns and processes information (Oakley et al., 2021; Oakley and Sejnowski, 2019). These developments have identified evidence-based learning strategies with transformative potential to enhance educational outcomes, as demonstrated by a growing body of empirical research showing consistent gains in learning retention, conceptual understanding, and the transfer of knowledge across domains (Narkhede et al., 2024). Meta-analyses and experimental studies conducted in diverse fields - including STEM education (Wissman & Leontyev, 2024), medical training (Martínez & Gómez, 2025), and second language learning (Frans & Wahani, 2025) - indicate that strategies such as spaced practice, retrieval-based learning, and self-explanation outperform traditional rote learning approaches by fostering deeper cognitive engagement, long-term retention, and more flexible application of knowledge.

Effective learning transcends the acquisition of factual knowledge, emphasizing integrating, application, and transfer of knowledge across contexts (Carpenter et al., 2022). Two key concepts underpin this process: knowledge retention and knowledge transfer (Barnett & Ceci, 2002). Retention refers to the ability to store and recall information, forming the basis of learning. Transfer involves applying a deeper understanding of concepts to new and diverse situations, which is an essential capacity for meaningful learning. While mastering foundational skills (e.g., mathematical principles, vocabulary, taxonomies) is crucial, the ultimate goal of education is to foster the ability to creatively and effectively adapt and apply knowledge.

Research highlights significant variability in the effectiveness of different learning techniques. Dunlosky et al. (2013) conducted a comprehensive review of ten widely used or extensively studied methods, identifying distributed practice and practice testing as the most effective strategies for promoting long-term learning. Distributed practice involves spacing learning sessions over time, leveraging the well-established spacing effect (Cepeda et al., 2008). Practice testing, which includes self-assessment or and low-stakes quizzes, engages active recall, strengthening memory pathways and deepening comprehension (Adesope et al., 2017; Rawson & Dunlosky, 2011).

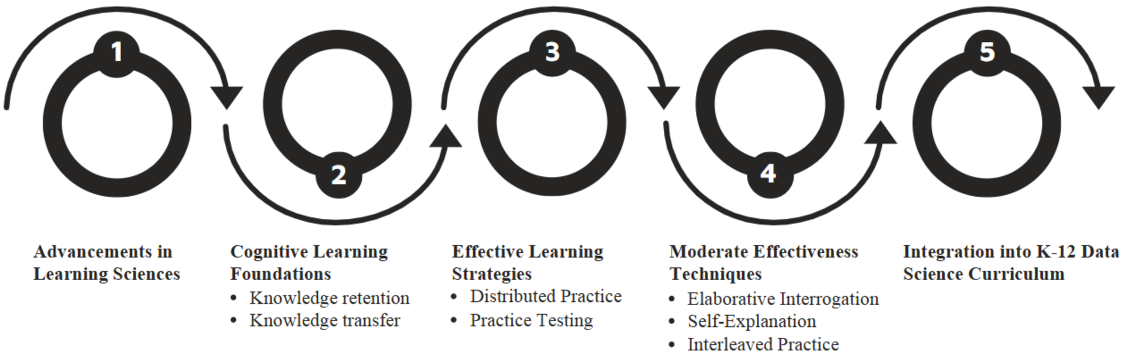
These strategies demonstrate their effectiveness across diverse learning contexts, including various types of material (e.g., vocabulary, science definitions or mathematical procedures), learning conditions (individual or. group study), learner characteristics (age, prior knowledge), and learning goals (e.g., essay writing, analytical argumentation). Moreover, combining distributed practice with practice testing yields even greater benefits (Hopkins et al., 2016; YeckehZaare et al., 2019).

Other techniques, such as elaborative interrogation, self-explanation, and interleaved practice, have shown moderate effectiveness. Interleaving, in particular, which alternates between topics or problem types, enhances skills such as differentiation and flexible application (Chen et al., 2021). Conversely, summarization, highlighting, keyword mnemonics, imagery for text learning, and rereading received low utility ratings due to generalizability.

Integrating these findings into a K-12 data science curriculum (Figure 1) requires designing engaging, age-appropriate activities that embed proven learning strategies. A well-designed course can be structured around the four core stages of the data science process: data collection, preprocessing, analysis, and visualization (Barany et al., 2024), ensuring that students acquire both foundational knowledge and practical experience.

Figure 1

Integrating learning strategies into K-12 Data Science Curriculum



Source: Authors (2026).

In the context of data collection, distributed practice involves introducing students to multiple methods over time (e.g., surveys, web scraping, sensor-based data collection). Revisiting these methods through recap activities or mini-projects reinforces retention. Practice testing can involve creating mock datasets or identifying errors in simulated data-collection processes, fostering active engagement and familiarizing students with real-world challenges.

For data preprocessing, distributed practice allows students to revisit essential techniques such as handling missing data, normalizing, and outliers detection across multiple sessions. Using datasets from diverse domains (e.g., sports, environment) enhances generalization. Practice testing may include quizzes or hands-on exercises that require cleaning and preprocessing increasingly complex datasets, promoting skill mastery and confidence.

Similarly, data analysis and data visualization benefit from structured and interactive application of these strategies. Analytical techniques (e.g., measures of central tendency, correlation, regression) and visualization tools (e.g., bar charts, scatter plots, histograms) can be introduced progressively and revisited periodically. Practice testing may involve interpreting analytical results or improving flow visualizations through low-stakes assessments that reinforce understanding and mirror practical problem-solving.

By integrating distributed practice and practice testing across teaching of data collection, preprocessing, analysis, and visualization, students might gain deeper conceptual understanding and develop the ability to retain and apply knowledge effectively. This approach supports comprehensive and enduring learning that equip students to navigate the full data science process.

4 ASSESSMENT AND EVALUATION STRATEGIES

Learning assessment plays a strategic role in the pedagogical process, particularly when adapting instruction based on evidence (Black & Wiliam, 1998; Lolkus et al., 2022). A formative approach, grounded in learning sciences research, supports progress monitoring while fostering autonomy, metacognition, and conceptual understanding.

Unlike summative assessments, which verify performance at the end of a cycle, formative assessment is continuous, diagnostic, and integrative. It occurs during the learning process, enabling teachers to adjust instruction, provide targeted feedback, and intervene pedagogically when needed (Sadler, 1989; Brookhart, 2013). The emphasis shifts from outcomes to the process of knowledge construction.

Meta-analyses indicate that practices such as short quizzes with immediate feedback and structured self-explanations have significant positive effects, especially when integrated into routine classroom cycles (Yang et al., 2022; Latimier et al., 2021). These practices promote active student engagement, support retrieval processes, and strength metacognition (Yang et al., 2022). When systematically embedded in instructional design, these same practices also function as formative assessment mechanisms, generating actionable evidence that informs both teaching decisions and student self-regulation.

With this perspective, teachers assume an expanded role: they become designers of assessment strategies and interpreters of learning evidence (Kenney et al., 2022). This work requires technical expertise, requires time for planning, and institutional support, especially in emerging fields such as data science.

Among the most promising assessment tools are analytic rubrics, which specify criteria for different performance levels in complex tasks. Analytic rubrics break down a task into distinct criteria, offering quality descriptions for each one, which allows teachers to provide students with more detailed feedback on their strengths and areas that need improvement.

When shared with students, rubrics foster self-regulation, clarify objectives, and support the internalization of quality standards (Brookhart, 2013; Panadero & Jonsson, 2013). For this to occur effectively, it is not enough to simply distribute the instrument; it is necessary to design activities that actively engage students with the rubric, such as self-assessment, in which students compare their own work with the rubric descriptions to set progress goals. In this process, the rubric translates learning intentions into accessible language, enabling students to understand not only the task but also the content and the qualities of “good work”.

In data science, rubrics can be applied to evaluate data projects, visualization, interpretive reports, and other authentic tasks. Considering that competencies such as data reasoning, statistical literacy, computational thinking, and ethical judgment in data-driven contexts are among the core and fastest-growing competencies for the future, the use of rubrics makes it possible to align assessment with these complex learning objectives, serving both formative purposes (guidance) and summative purposes (grading).Technological innovations have expanded the scope of formative assessment. Recent studies explore the use of artificial intelligence and natural language processing (NLP) tools to generate automated feedback on open-ended tasks (Lloyd et al., 2022). These innovations support scalability and personalization, especially in contexts characterized by teaching load or heterogeneous learning needs.

However, assessment must reflect the complexity of data science. Instruments that emphasize only mathematical accuracy or visual aesthetics fail to capture competencies such as statistical reasoning, critical interpretation, decision-making, and evidence-based communication. Instead, assessment must address the cognitive, procedural, and attitudinal dimensions across the entire data cycle.

Evidence-based formative assessment offers a promising pathway for consolidating data science learning in basic education. By integrating tools such as rubrics, feedback-driven quizzes, structured self-explanations, schools can create more responsive and equitable environments aligned with the competencies required for scientific and digital citizenship.

Effective implementation of evidence-based formative assessment strategies in DS education requires overcoming pedagogical, institutional, and cultural obstacles. Although cognitive psychology and learning sciences highlight the benefits of spaced practice, retrieval testing, and self-explanation (Dunlosky et al., 2013; Latimier et al., 2021), their systematic adoption in school remains limited, especially in public systems with constrained resources.

A central barrier is insufficient teacher preparation. Many teachers lack adequate training, whether in initial certification or ongoing professional development, to apply formative assessment principles or evidence-based strategies (Darling-Hammond et al., 2017; Freitas, 2020). As a result, summative approaches dominate, oriented toward performance measurement rather than instructional improvement (Sadler, 1989; Mogboh & Okoye, 2019).

Structural factors exacerbate this scenario: limited pedagogical time, bureaucratic overloads, and the lack of collaborative spaces for teacher dialogue. School culture centered that equate assessment with standardized tests often resist more dynamic approaches, such as portfolios, rubrics, classroom observations, and formative feedback cycles (Andrade, 2005; Soares et al., 2025).

Nonetheless, new opportunities are emerging. The increasing emphasis on personalized learning, competency-based education, and data-informed instruction provides favorable context for redefining assessment as an integral component of learning (Andrade & Cizek, 2010). In this framework, teachers act as mediators, not merely an executor of standardized instruments but acts as a qualified mediator capable of interpreting evidence and adapting instruction (Hattie & Timperley, 2007).

Analytic rubrics are particularly promising. When well designed, they clarify performance criteria, support self-assessment, and establish a shared vocabulary of expectations (De Campos & Ferreira, 2024; Panadero & Jonsson, 2013). In DS education, rubrics can be applied to projects involving data analysis, visualizations, interpretation, and communication.

Consolidating this approach requires policies that invest in teacher professional development, promote evidence-based instructional decision-making, and support learning communities (Desimone & Garet, 2015). Teachers must be recognized as central agents of assessment, with access to time, technical support, and autonomy (Freitas, 2018).

Finally, the timing of assessment is crucial. Research on distributed learning shows that review intervals significantly influence long-term retention. Cepeda et al. (2008) demonstrated that the optimal spacing varies with desired retention for a week, while retaining knowledge for a year requires intervals of 21 to 27 days. Therefore, assessment schedules should be strategically aligned with expected knowledge retention windows. Tests administered immediately after intensive often overestimate learning; to assess durable understanding, evaluations must account spacing principles.

5 IMPLEMENTATION CHALLENGES: FOUNDATIONAL GAPS AND SYSTEMATIC BARRIES

Introducing data science (DS) into basic education involves challenges that extend beyond curriculum design. These include structural gaps in foundational learning, limitations in teacher training, and barriers to implementing evidence-based assessment. This section explores two key dimensions: (1) gaps in foundational knowledge that hinder DS learning, and (2) barriers to adopting evidence-based formative assessments.

The major challenge in advancing data science education for K-12 students is addressing persistent gaps in foundational knowledge (Figure 2). Global learning

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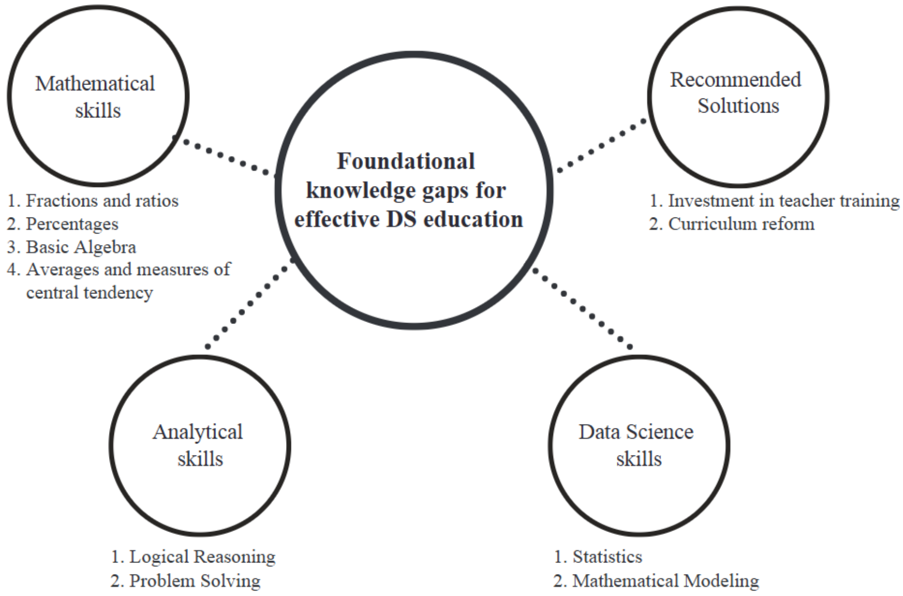
assessments reveal concerning trends. According to the Programme for International Student Assessment (PISA) 2022, student performance across OECD countries experienced an unprecedented decline, with drops of 10 points in reading and nearly 15 points in mathematics relative to 2018, equating to roughly three-quarters of a year of learning loss (OECD, 2023). This decline, the largest consecutive drop on record, underscores the urgency of strengthening basic skills alongside introducing emerging topics such as data science.

Figure 2

Examples of gaps in foundational knowledge



Source: Authors (2026).

Alarmingly, one in four 15-year-olds in OECD countries now struggle with fundamental tasks such as applying simple algorithms or interpreting basic texts. In 18 countries, more than 60% of 15-year-old students lag behind in mathematics, reading, and science. While the COVID-19 pandemic intensified these issues, the downward trend predates it: countries such as Belgium, Canada, Finland, France, and the Netherlands were already showing declining mathematics performance before 2018.

In low- and middle-income countries, the situation is even more severe. Although school attendance has increased, improvements in learning outcomes remain limited (Duflo et al., 2020). In India, the Annual Status of Education Report (ASER) reveals that more than half of rural students aged 14-18 struggle with basic division (Bhattacharyya, 2023). In Ghana, only about 25% of students reach proficiency in English and mathematics (Duflo et al., 2020). In Brazil, only 18.2% of students demonstrate adequate learning in science and

12.3% in mathematics, while in OECD countries these proportions reach 50.7% in science and 48.2% in mathematics (QEdu, 2024).

These trends highlight the critical importance of foundational mathematical skills for DS education. Core mathematical concepts, such as fractions, ratios, percentages, algebra, and measures of central tendency, are essential for statistical reasoning, data interpretation, and algorithmic thinking. Without these foundations, students struggle to understand probability, modeling, regression, or even simple data exploration.

Basic algebra also plays a vital role in data science applications, providing the tools to work with equations and formulas. Solving linear equations, for example, helps students understand variable relationships, a necessary skill for modeling and predictive analytics. Without a solid foundation, more advanced topics such as regression analysis and machine learning algorithms remain inaccessible.

Skills like calculating and interpreting measures of central tendency, including mean, median, and mode, are also foundational. These concepts, introduced in early mathematics education, become indispensable in data science for summarizing datasets, exploring trends, and deriving meaningful insights from data. Additionally, logical reasoning and problem-solving, often developed through mathematics, are fundamental to programming, algorithm design, and debugging. These cognitive skills enable students to approach complex problems methodically, a core competency in data science workflows.

The persistence of these deficiencies demonstrates the need for systematic investment in teacher preparation, curriculum reform, and equitable resource distribution. Although data science offers innovative pathways for engagement, it cannot compensate forthe absence of essential foundational learning. Sustainable improvements requires long-term strategies that prioritize core skills while integrating modern disciplines such as data science.

6 IMPLEMENTATION CHALLENGES: FOUNDATIONAL GAPS AND SYSTEMATIC BARRIES

This study proposes an evidence-based learning assessment model designed for implementing a data science educational intervention. The model systematically tracks student progress, capturing gains in theoretical and practical knowledge, core skills (e.g., mathematics and reading), and levels of motivation and engagement. Beyond measuring outcomes, the assessments also identify challenges and best practices that inform effective implementation. By integrating pedagogical strategies, such as spaced and retrieval practice, with mixed-method assessment tools, the model provides a structured framework for evidence-informed teaching and decision-making, supporting the design of innovative education policies.

Table 1 outlines an example of implementation of this educational framework designed to effectively teach key data science concepts. Each row pairs specific content with clear objectives, emphasizing both theoretical understanding and practical application. For instance, students learn not only how to create graphs and interpret trends but also how to apply their knowledge to real-world contexts, such as developing recommendation systems or analyzing public health data.

Table 1

Educational framework designed to teach data science concepts

Content	**Objective**	**Distributed practice**	**Practice testing**
Introduction to data Science	Build the definition of data science starting from the definition of the statistical question and exploring the data cycle.	Week 1 Week 4 (time to revisit)	Cards about statistical question. Creating a recommendation system while exploring the data cycle.
Data organization	Identify types of variables, discuss the ubiquity of data in structured or unstructured forms, and explore methods for data collection and organization.	Week 2 Week 3 Week 6 (time to revisit)	Cards about types of variables. Collect data from texts and images.
Data visualization	Understand how to explore data by constructing graphs.	Week 4 Week 5 Week 10 (time to revisit)	Collect data and create graphs. Storytelling quiz with data.
Correlation	Understand and perceive correlations between bivariate data.	Week 6 Week 7 Week 11 (time to revisit)	Practical Project to explore correlations. Dancing correlations.
Measures of central tendency	Recognize mean, mode and median.	Week 8 Week 9 Week 12 (time to revisit)	Summarize public safety data. Short-answer questions.

Probability	Propose a question about the probability of data	Week 10 Week 11 Week 14 (time to revisit)	Case Study Analysis on Public Health. Short-answer question.
Sample survey and Hypothesis Testing	Observe and understand the collection of information about a population through a representative sample.	Week 12 Week 13 Week 16 (time to revisit)	Free recall about cases discussed (e.g., solid waste, influencers and gender, elections).
Linear regression	Analyse a problem and use graph visualization and regression models to identify trends for decision-making.	Week 14 Week 152* Week 19 (time to revisit)	Development of a Regression Model Project (eg., focused on urban mobility).

Source: Authors (2026).

In practical terms, Table 1 functions as a pedagogical planning tool that supports teachers in organizing instruction, assessment, and revision cycles in a coherent and evidence-informed manner. By explicitly mapping content, learning objectives, moments of distributed practice, and retrieval-based activities, the table helps teachers anticipate when key concepts should be introduced, revisited, and assessed. This structure enables educators to move beyond linear content coverage and adopt a cyclical approach to teaching, in which instructional decisions are guided by evidence about retention, transfer, and student progress. Moreover, the table can be adapted to different school contexts, time constraints, and student profiles, serving both as a curriculum design reference and as a flexible guide for classroom implementation.

The framework incorporates distributed practice, which spaces learning sessions over time to reinforce retention. For example, topics like "Data Visualization" and "Measures of Central Tendency" are revisited across multiple weeks, allowing students to deepen their understanding incrementally. This approach leverages the spacing effect, ensuring repeated exposure to key concepts, thereby enhancing long-term retention.

Additionally, practice testing actively engages students in applying what they have learned. Activities range from creating datasets to developing case studies and participating in storytelling exercises using data. By emphasizing active recall and problem-solving, practice testing strengthens memory pathways and fosters deeper comprehension. Structured feedback sessions following these activities further reinforce correct understanding and address misconceptions.

To systematize formative assessment, competency-based rubrics were developed (Table 2) to guide the evaluation of data science projects (such as graph construction, correlation analysis, or hypothesis formulation). Each rubric includes four performance levels (Beginner, Basic, Proficient, and Advanced), which allow the teacher to monitor student progress, adjust teaching interventions, and provide qualitative feedback.

The adoption of rubrics in daily school life allows teachers to qualify and enhance their assessment practices, providing students with clear indicators of progress. Furthermore, it creates a culture of continuous feedback that values the learning process, aligned with the guidelines of formative assessment. These rubrics can also be used as tools for planning, self-assessment, and collaboration among teachers.

The pedagogical approach combines these two strategies to maximize learning outcomes. Distributed practice ensures students retain foundational concepts over time, while practice testing promotes critical thinking and the ability to apply knowledge effectively. Together, these tools strengthen the coherence between instruction and evaluation. The framework covers key aspects of data science, from foundational concepts to advanced topics, ensuring a comprehensive understanding of the field. It integrates real-world relevance by engaging students in authentic tasks. By focusing on practical applications, the framework equips students with the confidence and skills needed to tackle real-world challenges.

7 EVIDENCE-BASED VALIDATION

Validating any educational framework requires not only conceptual analysis but also robust empirical evidence. In the case of Data Science in Basic Education, this implies verifying the extent to which teaching data science and integrating effective learning strategies, such as distributed practice and retrieval testing, results in measurable gains in performance, engagement, and the development of cognitive and socio-emotional skills.

Table 2

Framework of competencies and performance indicators for assessing data literacy

Competency	Level 1 – Beginner	Level 2 – Basic	Level 3 – Proficient	Level 4 – Advanced

1. Data Cycle	Does not recognize the stages of the data cycle or confuses their order.	Recognizes some stages of the data cycle, but with imprecise order or functions.	Correctly identifies all stages and their functions.	Relates the stages to concrete situations in school or daily life.
2. Data Organization	Has difficulty organizing data or distinguishing variables.	Partially understands how data can be organized in tables.	Organizes data into tables clearly and consistently.	Interprets and creates data structures with multiple variables and context.
3. Data Visualization	Does not recognize types of charts or their uses.	Identifies basic charts but has difficulty interpreting them.	Correctly interprets bar, pie, and line charts.	Selects and interprets appropriate charts in different contexts.
4. Correlation	Does not understand the concept of correlation.	Recognizes positive or negative correlation in simple examples.	Confidently distinguishes positive, negative, and zero correlation.	Interprets correlation in real data and identifies spurious correlations.
5. Measures of Central Tendency	Does not understand mean, mode, or median.	Calculates simple measures with occasional errors.	Correctly calculates mean, mode, and median.	Interprets and compares measures across different datasets.
6. Probability	Does not understand the concept of chance or probability.	Recognizes simple probabilities but with conceptual errors.	Solves probability problems in everyday situations.	Applies probabilistic reasoning in varied contexts and makes informed decisions.
7. Hypothesis Testing	Does not understand the concept of a hypothesis in data science.	Recognizes a hypothesis and understands that it can be tested.	Understands the null hypothesis and how to make decisions based on data.	Formulates appropriate hypotheses and interprets results based on evidence.

8. Sampling Research	Confuses population with sample or does not understand the need for sampling.	Recognizes the difference between population and sample, but with limitations.	Explains and uses basic sampling strategies.	Justifies sampling choices in applied research contexts.
9. Linear Regression	Does not understand the idea of relationships between variables.	Recognizes simple visual relationships in charts.	Interprets linear relationships and understands the concept of prediction.	Explains dependence between variables based on real contexts and charts.

Source: Authors (2026).

The implementation of innovative pedagogical strategies in DS courses should be accompanied by rigorous impact evaluations capable of isolating the causal effects of the intervention. Unlike retrospective evaluations, which are more susceptible to bias, prospective designs, such as randomized controlled trials (RCTs) and well-structured quasi-experiments (difference-in-differences, for example), allow for the establishment of valid counterfactuals and the reliable attribution of observed results to the implemented framework (Gertler et al., 2016; Duflo et al., 2007).

A critical element of this process is the construction of a theory of change and a chain of results (Mayne, 2017). This approach maps the link between inputs, activities, outputs, intermediate results, and short-, medium-, and long-term impacts. In addition to guiding the measurement of results, this resource makes explicit the mechanisms by which the framework should produce effects, strengthening the explanatory validity of the evaluation.. Complementing this is the process of defining evaluation questions, such as "Does this intervention improve students' ability to summarize data into graphs?" or “Does it encourage students to reflect beyond their own experiences through statistical analysis?” Additionally, selecting appropriate outcomes and performance indicators aligns evaluation efforts with the program's goals.

Previous studies demonstrate the potential of rigorous methodologies. For example, a randomized controlled trial (RCT) conducted in Ghana (Duflo et al., 2020) showed significant gains in after-school programs, while the experiment by Boaler et al. (2018) in California showed that online courses based on growth mindset improved math performance by 0.33 standard deviations. These examples reinforce that the adoption of RCTs or quasiexperimental designs in growth mindset education can offer reliable evidence for public policies and pedagogical practices.

However, conducting impact evaluations of educational interventions faces significant structural difficulties. The diversity of school contexts, teacher turnover, the influence of external factors (such as concurrent public policies), and the time required to observe sustainable effects represent challenges for causal attribution. In addition, the inherent costs, from large-scale data collection to longitudinal student follow-up, can be significant, especially in educational systems with budgetary constraints.

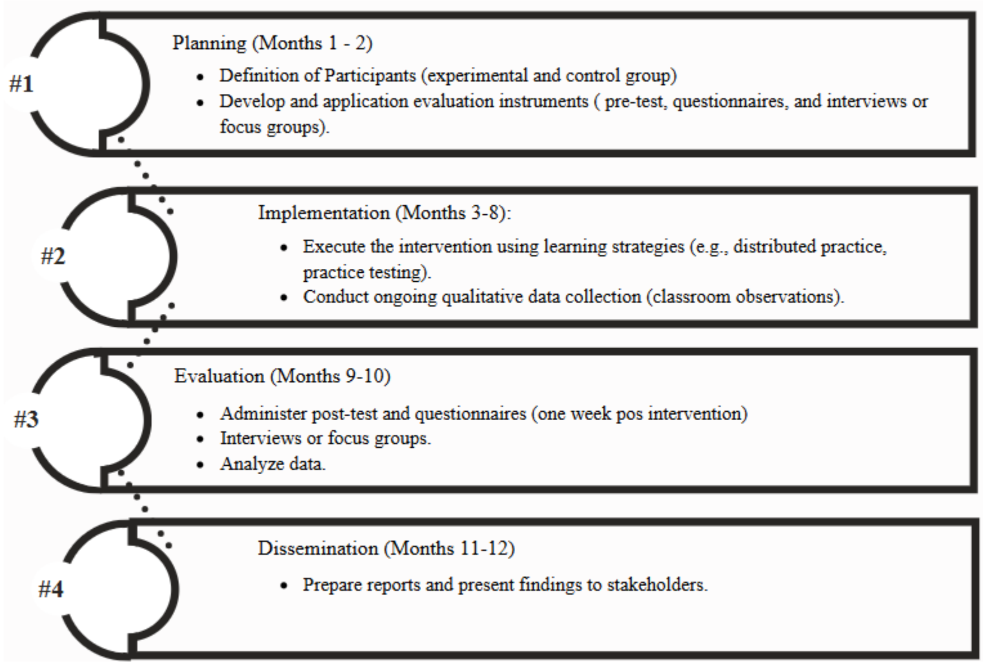
Even in the face of these barriers, conducting the evaluation is important. In a scenario of scarce resources, impact evidence allows us to identify which components of the framework are most effective and therefore deserve greater investment. Furthermore, it makes it possible to reduce waste, adjust implementation strategies, direct training structure for implementers, and increase the efficiency of public policies. In this sense, impact evaluation should not be seen merely as an additional cost, but as a strategic investment to ensure the sustainability, legitimacy, and scalability of innovative proposals.

In the context of the proposed framework, the use of mixed methods for conducting impact evaluation is recommended. Standardized tests, questionnaires, performance rubrics, and engagement metrics should be combined with classroom observations, interviews, reflective portfolios, and learning journals. This triangulation broadens the understanding of the effects, capturing both quantitative results and qualitative transformations in teaching practice and student development, consistent with established mixed-methods evaluation frameworks in education (Creswell & Plano Clark, 2018).

Initiating an impact evaluation in data science requires a structured approach, beginning with the definition of the evaluation question (hypothesis) and the development of a theory of change, followed by a systematic process divided into four main phases (Figure 3). The first phase, Planning (Months 1-2), focuses on the initial preparation of the intervention. Participants are identified and assigned either to the control or the treatment group. Evaluation instruments such as pre-tests, questionnaires, interviews, and focus groups are developed and applied to gather pre-intervention data, ensuring clear objectives and appropriate tools for the evaluation process.

Figure 3

Pilot course evaluation schedule



Source: Authors (2026).

During the second phase, Implementation (Months 3-8), the educational program is carried out, and qualitative and quantitative data are collected. Continuous classroom observations are conducted to document the implementation process, identify dynamics, and understand the challenges and opportunities associated with the intervention. In the Evaluation (Months 9-10) phase, the intervention's outcomes are analyzed using data collected before, during, and after the intervention. These data are gathered through instruments, including tests, questionnaires, interviews, and focus groups to assess changes in participants' knowledge, skills, and attitudes. The data analysis workflow for the RCT will largely depend on the sample size and the degree of noncompliance observed, as mentioned in Section 4.2.

The final phase, Dissemination (Months 11-12), aims to share the evaluation results with stakeholders. Reports summarizing the findings are prepared in a clear and accessible format, and the results are presented to stakeholders such as schools, policymakers, and educators. This phase ensures transparency in the process and provides valuable insights that can inform future decisions, refine the intervention, or scale it to other contexts.

More than a measurement exercise, impact evaluation should be conceived as a feedback mechanism. By providing systematic evidence of the framework's effectiveness, it enables continuous adjustments, increases the legitimacy of the proposal, and strengthens its applicability in diverse contexts. Thus, the validation of the framework is not limited to proving its effectiveness, but contributes to transforming it into a scalable, evidence-driven, and economically viable innovation tool for Basic Education.

8. Conclusion: Toward a Sustainable Data-Informed Curriculum

This research highlights the critical importance of integrating learning strategies and assessment methodologies for teaching data science in Basic Education. Rather than addressing these elements in isolation, this study contributes an integrated, evidence-based framework that explicitly aligns teaching strategies, learning progressions, and formative assessment instruments within a coherent pedagogical model. In a data-driven era, it is essential to prepare students to interpret, analyze, and communicate information critically and responsibly. To achieve this, it is not enough to include new content: it is necessary to adopt pedagogical practices that promote deep and lasting learning and translate findings from cognitive and learning sciences into operational guidance for classroom practice.

By addressing gaps in fundamental knowledge and applying evidence-based practices, such as distributed practice and retrieval-based testing, the proposed framework offers a robust path to foster theoretical understanding and practical application among students. A distinctive contribution of this work lies in demonstrating how these learning principles can be systematically embedded into instructional planning and assessment routines, rather than remaining as abstract recommendations.

The findings highlight the transformative potential of data science education for the development of analytical, communicational, and ethical competencies among students. However, this potential is only realized through sustained investments in teacher training, curriculum reform, and a strengthened culture of formative assessment. This study advances literature by positioning formative assessment not merely as a measurement tool, but as a central pedagogical mechanism that supports learning, equity, and instructional decision-making in data science education.

In short, the integration of learning strategies and formative assessment represents a concrete step forward in building more effective, equitable, and sustainable data science curricula. Beyond consolidating existing evidence, the framework proposed here offers a practical and transferable structure that can be adapted across diverse educational contexts. This integration strengthens teaching practice, enhances the pedagogical use of data, and promotes student protagonism. Achieving this vision, however, requires a coordinated effort among teachers, administrators, researchers, and public policy makers. More than a technical proposal, it is a cultural transformation that repositions the student at the center of the educational process and values the teacher as a critical agent of change.

It is recognized, however, that the validation of the framework requires rigorous and feasible impact assessment processes. Randomized controlled trials (RCTs) and quasi-experiments offer internal validity but face ethical, financial, and contextual limitations. By articulating a clear evaluation logic aligned with the proposed pedagogical framework, this study contributes to ongoing debates on how to balance methodological rigor and practical feasibility in educational innovation. In this regard, mixed-method and alternative low-cost approaches represent promising paths to combining methodological rigor and practical relevance.

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REFERENCES

Adesope, O.O., Trevisan, D.A., Sundararajan, N. (2017). Rethinking the Use of Tests: A Meta-Analysis of Practice Testing. Review of Educational Research, 87, 659–701. https://doi.org/10.3102/0034654316689306

Adisa, I.O., Herro, D., Abimbade, O., Arastoopour Irgens, G. (2024). Engaging elementary students in data science practices. Information and Learning Sciences, 125, 513–544. https://doi.org/10.1108/ILS-06-2023-0062

Andrade, H. (2005). Teaching with rubrics: The good, the bad, and the ugly. College Teaching, 53(1), 27–30. https://doi.org/10.3200/CTCH.53.1.27-31

Andrade, H. & Cizek, G. J. (2010). Handbook of formative assessment. Routledge.

Barany, A., Scarola, A.D., Acquah, A., Reza, S.M., Johnson, M.A., Walker, J. (2024). Learning designs that empower: navigating sandbox data science at the intersection of computing, big data and social media. Information and Learning Sciences, 125, 794–812. https://doi.org/10.1108/ILS-12-2023-0211

Barnett, S.M., Ceci, S.J. (2002). When and where do we apply what we learn?: A taxonomy for far transfer. Psychological Bulletin, 128, 612–637. https://doi.org/10.1037/0033-2909.128.4.612

Bhattacharyya, R. (2023). Annual Status of Education Report (ASER 2023: Beyond Basics).

Black, P., & Wiliam, D. (2010). Inside the black box: Raising standards through classroom assessment. Phi Delta Kappan, 92(1), 81–90. https://doi.org/10.1177/003172171009200119

Boaler, J., Conte, K., Cor, K., Dieckmann, J.A., LaMar, T., Ramirez, J., Selbach-Allen, M. (2024). Studying the Opportunities Provided by an Applied High School Mathematics Course: Explorations in Data Science. Journal of Statistics and Data Science Education, 1–20. https://doi.org/10.1080/26939169.2024.2333735

Boaler, J., Dieckmann, J.A., Pérez-Núñez, G., Sun, K.L., Williams, C. (2018). Changing Students Minds and Achievement in Mathematics: The Impact of a Free Online Student Course. Frontiers in Education, 3 https://doi.org/10.3389/feduc.2018.00026

Brookhart, S. M. (2013). Grading. In J. H. McMillan (Ed.), SAGE handbook of research on classroom assessment (pp.357–372). SAGE Publications. https://doi.org/10.4135/9781452218649.n15

Carpenter, S.K., Pan, S.C., Butler, A.C. (2022). The science of effective learning with spacing and retrieval practice. Nature Reviews Psychology, 1, 496–511. https://doi.org/10.1038/s44159-022-00089-1

Cepeda, N.J., Vul, E., Rohrer, D., Wixted, J.T., Pashler, H. (2008). Spacing effects in learning: A temporal ridgeline of optimal retention. Psychological Science, 19(11), 1095–1102. https://doi.org/10.1111/j.1467-9280.2008.02209.x

Chen, O., Paas, F., Sweller, J. (2021). Spacing and Interleaving Effects Require Distinct Theoretical Bases: a Systematic Review Testing the Cognitive Load and Discriminative-Contrast Hypotheses. Educational Psychology Review. https://doi.org/10.1007/s10648-021-09613-w

Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.

DataScience4Everyone, (2024). About our coalition [WWW Document]. https://www.datascience4everyone.org/about.

Darling-Hammond, L., Hyler, M. E., & Gardner, M. (2017). Effective teacher professional development. Learning Policy Institute.

De Campos, D. S., & Ferreira, D. J. (2024). Learning strategy regulation processes with rubrics for learning assessment. Revista Científica Sistemática, 14(4), 932–947. https://doi.org/10.56238/rcsv14n4-013

Desimone, L. M., & Garet, M. S. (2015). Best practices in teacher's professional development. Physics Teacher, 52(3), 38–47

Duflo, A., Kiessel, J., Lucas, A. (2020). Experimental Evidence on Alternative Policies to Increase Learning at Scale (NBER Working Paper No. 27298). National Bureau of Economic Research. https://doi.org/10.3386/w27298

Duflo, E., Glennerster, R., Kremer, M. (2007). Chapter 61 Using Randomization in Development Economics Research: A Toolkit. In Handbook of development economics (Vol. 4, pp. 3895–3962). Elsevier. https://doi.org/10.1016/S1573-4471(07)04061-2

Dunlosky, J., Rawson, K.A., Marsh, E.J., Nathan, M.J., Willingham, D.T., (2013). Improving students' learning with effective learning techniques: Promising directions from cognitive and educational psychology. Psychological Science in the Public Interest, 14(1), 4–58. https://doi.org/10.1177/1529100612453266

Firmino, C. R. S., Bijos, J. C. B. de F., Vasconcelos, C. F., Ardigó, R. M., & Oliveira-Esquerre, K. P. (2025). Meninas na ciência de dados: Empoderamento e equidade. Revista de Educação Pública. 4(3). https://doi.org/10.18264/repdcec.v4i3.348

Frans, N., & Wahani, V. (2025). Beyond the Classroom: Transformative Approaches in Learning Methods. Journal of English Language and Education, 10(3), 597–602. https://doi.org/10.31004/jele.v10i3.977

Freitas, L. C. (2018). A avaliação como mediação pedagógica. Cortez.

Freitas, L. C. (2020). Avaliação da aprendizagem: Um campo em disputa. Unesp.

Gertler, P., Martinez, S., Rawlings, L.B., Premand, P., Vermeersch, C.M.J., (2016). Impact Evaluation in Practice (2nd ed.). World Bank. https://doi.org/10.18235/0006529

Gould, R., Machado, S., Ong, C., Johnson, T., Molyneux, J., Nolen, S., Tangmunarunkit, H., Trusela, L., Zanontian, L. (2016). Teaching data science to secondary students: the mobilize introduction to data science curriculum. In: Promoting Understanding of Statistics about Society IASE Roundtable Conference. International Associatin for Statistical Education. https://doi.org/10.52041/SRAP.16402

Lloyd, K., Graesser, A., & Nye, B. D. (2022). Foundations for NLP-assisted formative assessment feedback for short-answer tasks. arXiv preprint arXiv:2205.02800. https://doi.org/10.48550/arXiv.2205.02829

Hattie, J., & Timperley, H. (2007). The power of feedback. Review of Educational Research, 77(1), 81–112. https://doi.org/10.3102/003465430298487

Heinemann, B., Opel, S., Budde, L., Schulte, C., Frischemeier, D., Biehler, R., Podworny, S., Wassong, T. (2018). Drafting a Data Science Curriculum for Secondary Schools. In: Proceedings of the 18th Koli Calling International Conference on Computing Education Research. ACM. https://doi.org/10.1145/3279720.3279737

Hopkins, R.F., Lyle, K.B., Hieb, J.L., Ralston, P.A.S., (2016). Spaced Retrieval Practice Increases College Students' Short- and Long-Term Retention of Mathematics Knowledge. Educational Psychology Review. 28, 853–873. https://doi.org/10.1007/s10648-015-9349-8

Kenney, J. L., Schroeder, C. M., & Carter, J. K. (2022). Developing formative assessment practices in instruction. Practical Assessment, Research & Evaluation, 27(1), 1–17. https://doi.org/10.7275/21376184

Kim, Y.M., (2021). The effects of pbl-based data science education program using app inventor on elementary students' computational thinking and creativity improvement. İlköğretim Online 20. https://doi.org/10.17051/ilkonline.2021.01.124

Komatsu, T., (2024). Evaluation, in: Education and Social Cohesion in a Post-Conflict and Divided Nation. Springer Nature Singapore, Singapore, pp. 143–146. https://doi.org/10.1007/978-981-99-6519-9_13

Latimier, A., Peyre, H., Ramus, F., (2021). A Meta-Analytic Review of the Benefit of Spacing out Retrieval Practice Episodes on Retention. Educational Psychology Review 33, 959–987. https://doi.org/10.1007/s10648-020-09572-8

Martínez, M. E., & Gómez, V. (2025). Active Learning Strategies: A Mini Review of Evidence-Based Approaches. Acta Pedagogia Asiana, 4(1), 43–54. https://doi.org/10.53623/apga.v4i1.555

Mayne, J., (2017). Theory of Change Analysis: Building Robust Theories of Change. Canadian Journal of Program Evaluation 32, 155–173. https://doi.org/10.3138/cjpe.31122

Mogboh, V., & Okoye, A. C. (2019). Formative and Summative Assessment: Trends and Practices in Basic Education. Journal of Education and Practice, 10(27), 39–45. https://www.iiste.org/Journals/index.php/JEP/article/download/49709/51356

Narkhede, K., Patil, R., Kasat, A., Gawas, A., & More, P. (2024). Unveiling the Art of Effective Learning through Spaced Repetition and Evidence-Based Techniques. In 2024 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS) (pp. 1–6). IEEE.. https://doi.org/10.1109/inc460750.2024.10649261

Oakley, B., Rogowsky, B., Sejnowski, T.J., (2021). Uncommon Sense Teaching: Practical Insights in Brain Science to Help Students Learn. Penguin Publishing Group.

Oakley, B.A., Sejnowski, T.J., (2019). What we learned from creating one of the world's most popular MOOCs. NPJ Science of Learning. https://doi.org/10.1038/s41539-019-0046-0

OECD, (2023). PISA 2022 Results (Volume I), PISA. OECD. https://doi.org/10.1787/53f23881-en

Olari, V., Romeike, R., (2024). Data-related concepts for artificial intelligence education in K-12. Computers and Education, 7, 100196. https://doi.org/10.1016/j.caeo.2024.100196

Panadero, E., & Jonsson, A. (2013). The use of scoring rubrics for formative assessment purposes revisited: A review. Educational Research Review, 9, 129–144. https://doi.org/10.1016/j.edurev.2013.01.002

QEdu. (2024). Brasil – Resultados do PISA 2022. Fundação Lemann; Fundação Roberto Marinho; Instituto Natura. Disponível em https://qedu.org.br/brasil

Rawson, K.A., Dunlosky, J., (2011). Optimizing schedules of retrieval practice for durable and efficient learning: How much is enough? Jounal of Experimental Psychology: General, 140, 283–302. https://doi.org/10.1037/a0023956

Sadler, D. R. (1989). Formative assessment and the design of instructional systems. Instructional Science, 18(2), 119–144. https://doi.org/10.1007/BF00117714

Schanzer, E., Pfenning, N., Denny, F., Dooman, S., Politz, J.G., Lerner, B.S., Fisler, K., Krishnamurthi, S., (2022). Integrated Data Science for Secondary Schools, in: Proceedings of the 53rd ACM Technical Symposium on Computer Science Education. ACM, New York, NY, USA, pp. 22–28. https://doi.org/10.1145/3478431.499311

Sharma, T., LePendu, P., (2022). Broadening Participation, in: Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 2. ACM. https://doi.org/10.1145/3545947.3576250

Soares, A. O., Diniz, G. K. S. da F., Dantas, M. L. F., Gundim, M. K. de M., & Almeida, E. (2025). Impactos e desafios das avaliações formativas e somativas no ensino à saúde. Revista Multidisciplinar Em Saúde, 6(3), 95–104. https://doi.org/10.51161/integrar/rems/4555

Walker, J.T., Barany, A., Acquah, A., Reza, S.M., Barrera, A., Del Rio Guzman, K., Johnson, M.A. (2023). Coding Like a Data Miner: A Sandbox Approach to Computing-Based Data Science for High School Student Learning. In 2023 IEEE Frontiers in Education Conference (FIE). IEEE, pp. 1–5. https://doi.org/10.1109/FIE58773.2023.10343283

Wissman, K. T., & Leontyev, A. (2024). Awareness and Implementation of Evidence-Based Learning Strategies Among STEM Faculty. The Journal of College Science Teaching, 1–10. https://doi.org/10.1080/0047231x.2024.2363118

Wolff, A., Gooch, D., Cavero Montaner, J.J., Rashid, U., Kortuem, G. (2016). Creating an Understanding of Data Literacy for a Data-driven Society. The Journal of Community Informatics 12. https://doi.org/10.15353/joci.v12i3.3275

World Economic Forum. (2025). Future of Jobs Report 2025 (Insight Report). Recuperado de https://www.weforum.org/reports/the-future-of-jobs-report-2025/

Yang, C., Luo, L., & Li, B. (2022). Testing (quizzing) boosts classroom learning: A systematic and meta-analytic review. Psychological Bulletin, 148(6), 464–483. https://doi.org/10.1037/bul0000313

YeckehZaare, I., Resnick, P., Ericson, B. (2019). A spaced, interleaved retrieval practice tool that is motivating and effective. In Proceedings of the 2019 ACM Conference on International Computing Education Research. ACM,. https://doi.org/10.1145/3291279.3339411