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Data-Driven Instructional Practices in Mathematics: The Role of Teacher Capacity and Institutional Support in Student Achievement in Nyarugenge District, Rwanda

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Abstract: *This study examined the relationships among data-driven instructional practices, teacher capacity, institutional support, and perceived student achievement in mathematics in public secondary schools in Nyarugenge District, Rwanda. The study was guided by Data-Driven Decision-Making (DDDM) Theory, the Theory of Planned Behavior (TPB), and the Technological Pedagogical Content Knowledge (TPACK) framework. A mixed-methods design was employed, involving 263 participants from 33 public secondary schools, including mathematics teachers, students, head teachers, and sector education officers. Data were collected using structured questionnaires and semi-structured interviews. The instruments demonstrated acceptable internal consistency, with Cronbach's alpha coefficients of 0.756 for teacher data-use skills, 0.716 for institutional support, and 0.725 for perceived student achievement. Teachers reported high self-perceived competence in data use (M = 4.17–4.52), although gaps remained in translating data-use skills into individualized instructional support. Institutional support was generally positive, particularly in teacher training, while comparatively weaker areas included feedback mechanisms, collaborative opportunities, and resource provision. Students similarly reported that assessment data were more consistently used for general instructional planning and monitoring than for individualized support. The study concludes that effective data-driven mathematics instruction requires the integration of teacher capacity, practical application of data, and sustained institutional support. It recommends strengthening school leadership, structured feedback mechanisms, collaborative practices, and sustained professional development to enhance the effective use of student data in mathematics instruction.*

Keywords: *Data-driven instruction, Mathematics achievement, Teacher capacity, Institutional support, Rwanda*

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1. Introduction

Quality education initiatives worldwide have increasingly emphasized data-driven instructional practices, particularly in mathematics, where the promise is straightforward: use evidence about how students are actually learning to shape how they are taught (Mandinach & Schildkamp, 2021). This emphasis has translated into policy mandates in many countries, pushing teachers toward formative assessment and learning analytics and away from instruction guided mainly by intuition (Schildkamp et al., 2019). Evidence from reform-oriented systems supports this approach: where teachers have genuine data literacy and work in institutions that support them, mathematics outcomes tend to improve meaningfully (Datnow & Park, 2019; Farley et al., 2018). However, a well-documented gap remains between what policy calls for and what happens in classrooms: many teachers lack the skills needed to translate data into concrete instructional decisions (Van et al., 2020).

Across Sub-Saharan Africa, interest in data-driven instruction has increased in response to persistent challenges in mathematics and numeracy outcomes (UNESCO, 2019). Although governments have invested in assessment systems and teacher professional development, implementation at the school level remains uneven (Kanjee, 2020). Evidence from Kenya and South Africa demonstrates the potential of effective school-level data use (Piper et al., 2018; Taylor & Spaull, 2020), while regional studies identify limited assessment literacy, inadequate instructional coaching, weak collaboration, and insufficient data-management systems as continuing constraints (Akyeampong et al., 2019; Bashir et al., 2018). These findings highlight the importance of strengthening both teachers' data-use capacity and institutional support for effective data-driven instruction.

In Rwanda, the Competence-Based Curriculum and increased emphasis on ICT integration provide a foundation for data-driven instruction, although evidence on its implementation remains limited (REB, 2020; MINEDUC, 2018). Persistent challenges in mathematics performance have contributed to greater emphasis on continuous assessment and school-level data use (NESA, 2019). However, limited evidence exists on how teachers' data-use knowledge and skills translate into classroom practices and how leadership, collaboration, and resource availability influence this process (Ndihokubwayo et al., 2022). Furthermore, few studies have examined the relationship between these teacher- and institutional-level factors and mathematics achievement (Uworwabayeho et al., 2019). This gap provides the basis for examining data-driven instructional practices in Nyarugenge District.

1.1 Statement of the Problem

Ideally, data-driven instructional practices would let mathematics teachers systematically use assessment evidence to identify learning gaps, adjust their teaching accordingly, and raise student achievement. That kind of system depends on pairing strong teacher data literacy with real institutional backing, things like regular coaching, collaborative data-review meetings, and management systems teachers can actually access so that improving mathematics mastery becomes a continuous cycle rather than a one-off effort. Nyarugenge District tells a different story, though. National learning assessment data from the past five years show that fewer than half of primary learners have demonstrated proficiency in foundational mathematics concepts, and district-level results haven't just stagnated; in some cycles, they've slipped slightly (NESA, 2019, 2022). This is despite Rwanda's clear policy commitment to competence-based curriculum and continuous assessment (MINEDUC, 2018). Classroom observations and inspectorate reports suggest that teachers largely collect achievement data because they're required to for administrative purposes, not because they use it to guide instruction. Many lack the analytical skills to turn raw scores into specific teaching decisions (Ndihokubwayo et al., 2022). This study addresses that gap.

1.2 Objectives of the Study

i. To investigate the teachers' knowledge and skills in use of data-driven instructional practices and impact on student achievement in mathematical concepts.
ii. To examine how institutional support structures shape teachers' implementation of data-driven instructional practices in mathematics and their impact on student learning outcomes.

1.3 Research Hypotheses

H_{01}: There is no significant relationship between teachers' knowledge and skills in the use of data-driven instructional practices and student achievement in mathematical concepts.
H_{02}: Institutional support structures do not significantly moderate the relationship between teachers' implementation of data-driven instructional practices and student learning outcomes in mathematics.

2. Literature Review

2.1 Theoretical Review

This study was anchored on Data-Driven Decision-Making (DDDM)) Theory, Theory of Planned Behavior (TPB) Ajzen (1991) and Technological Pedagogical Content Knowledge (TPACK) Framework as further explained in the following sub sections.

2.1.1 Data-Driven Decision-Making (DDDM)

While Data-Driven Decision-Making (DDDM) Theory provides the primary theoretical framework for this study, several complementary theories offer useful perspectives on data-driven instructional practices. Diffusion of Innovations Theory (Rogers, 2003) explains how innovative practices and technologies are adopted and disseminated within educational organizations; however, it provides limited explanation of how teachers interpret educational data and translate such evidence into specific instructional decisions. Organizational Learning Theory (Argyris & Schön, 1978) emphasizes collective reflection, knowledge development, and continuous organizational improvement, but is less specific about teachers' classroom-level use of assessment data to inform instruction. Similarly, Sensemaking Theory (Weick, 1995) provides insight into how teachers interpret and assign meaning to information through their professional experiences and interactions. Yet, it gives comparatively less attention to how these interpretations translate into instructional actions and subsequent learning outcomes. The Technology Acceptance Model (Davis, 1989) further explains individuals' acceptance and use of technology based primarily on perceived usefulness and ease of use; however, its focus is less directly concerned with the pedagogical processes through which teachers use educational data to improve teaching and learning. Consequently, although these theoretical perspectives provide valuable complementary insights, DDDM Theory is adopted as the primary framework because it directly emphasizes the systematic collection, interpretation, and application of educational data to guide instructional decisions and improve student learning outcomes.

Data-Driven Decision-Making (DDDM) was selected as the principal theoretical framework because it integrates data availability, teachers' data literacy, interpretation, instructional decision-making, and institutional support within an iterative process aimed at improving teaching and learning (Ansyari et al., 2020; Schildkamp & Poortman, 2015). DDDM explains how educational data are interpreted and translated into instructional actions and subsequently used to improve learning outcomes.

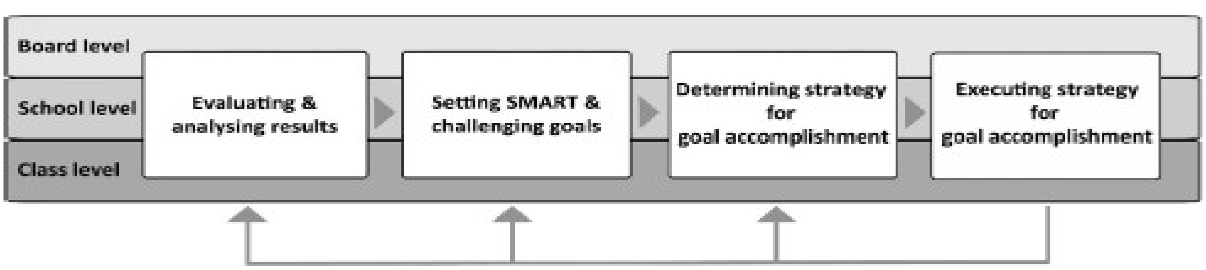
Effective data use depends not only on teachers' capabilities but also on enabling institutional conditions, including professional development, leadership support, collaboration, and accessible data systems (Mandinach & Jimerson, 2016; Schildkamp, 2019). DDDM is therefore appropriate for examining how mathematics teachers use educational data and how teacher capacity and institutional support facilitate or constrain data-driven instructional practices.

However, existing DDDM models may not fully account for contextual variations in teacher capacity, leadership support, and data infrastructure, particularly in resource-constrained settings (UNESCO, 2022; OECD, 2020). Accordingly, this study applies DDDM contextually by emphasizing teacher data literacy and institutional support as key factors influencing the translation of educational data into instructional practices and mathematics learning outcomes.

Conceptually, the proposed process is represented as follows:

Data Availability → Teacher Data Literacy and Interpretation → Instructional Decision-Making → Instructional Adaptation → Mathematics Learning Outcomes

Within this process, leadership support, professional development, teacher collaboration, and data infrastructure operate as contextual enabling or constraining factors. The proposed framework therefore extends the application of DDDM by explicitly recognizing the institutional and resource conditions within which teachers engage with educational data. It provides a basis for understanding data-driven mathematics instruction in the present study and offers a framework that may be examined further across diverse educational and resource contexts. The proposed model is presented in Figure 1.



The Four-Component Model

Note. From "On the Value of Data-Based Decision Making in Education: The Evidence From Six Intervention Studies," by A. J. Visscher, 2021, *Studies in Educational Evaluation*, *69*, p. 3. Copyright 2021 by the author. CC BY license.

As shown in Figure 1, the Data-Driven Decision-Making (DDDM) process consists of four main components: evaluating and analyzing results; setting specific, measurable, achievable, relevant, and time-bound (SMART) and challenging goals; identifying strategies to achieve the goals; and implementing the identified strategies. These components can be applied at three organizational levels classroom, school, and school board allowing data-driven decision-making to be coordinated across different levels of educational management (Keuning et al., 2019; Staman et al., 2017; van der Scheer et al., 2017; van der Scheer & Visscher, 2016, 2018; van Geel et al., 2016, 2017; Visscher, 2021).

2.1.2 Technological Pedagogical Content Knowledge (TPACK) Framework

The Theory of Planned Behavior (TPB), developed by Ajzen (1991), explains behavior through behavioral intentions shaped by attitudes, subjective norms, and perceived behavioral control. In this study, TPB provides a complementary perspective for understanding mathematics teachers' attitudes toward data use and their willingness to incorporate data-driven practices into instructional decision-making. However, because the study focuses more broadly on the processes and institutional conditions supporting educational data use, DDDM remains the principal theoretical framework.

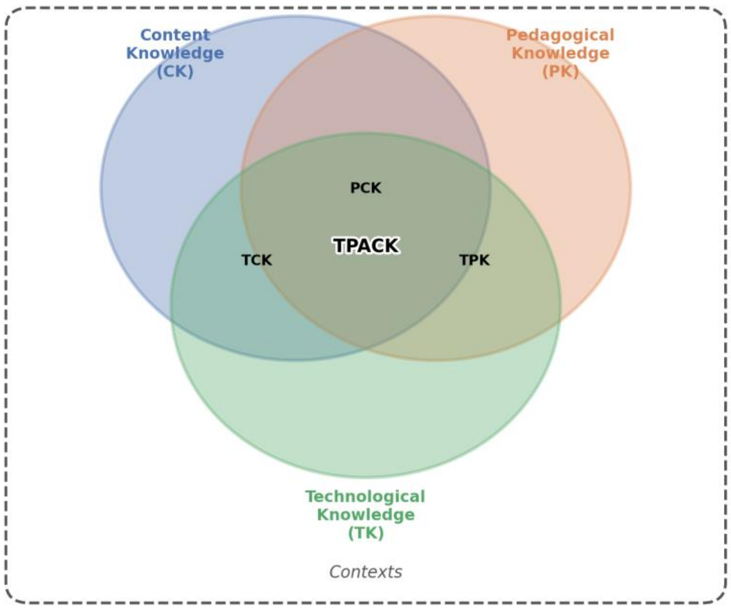


Figure 2: The TPACK Framework

Note. The TPACK framework illustrates the interaction among Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK), including their intersecting domains: PCK, TCK, TPK, and TPACK, within a broader contextual environment. Adapted from Mishra and Koehler (2006).

The TPACK framework emphasizes that effective technology integration requires teachers to combine technological, pedagogical, and content knowledge (Mishra & Koehler, 2006; Koehler et al., 2017). Although TPACK supports teachers' effective use of digital tools (Tondeur et al., 2018), it has been criticized for conceptual overlap among its domains, measurement challenges, and limited attention to institutional factors such as leadership, resources, and professional development (Willermark, 2018). Alternative frameworks, including SAMR, DigComp, and Diffusion of Innovations Theory, address technology use, digital competence, or innovation adoption but do not directly integrate content, pedagogy, and technology (Rogers, 2003; Vuorikari et al., 2022). Therefore, TPACK complements DDDM by explaining teachers' preparedness to integrate digital data tools with mathematics content and pedagogy, while DDDM provides the broader perspective for understanding how teacher capacity and institutional support influence data-driven instructional decision-making.

2.2 Mathematical Error Analysis and Data-Driven Instruction

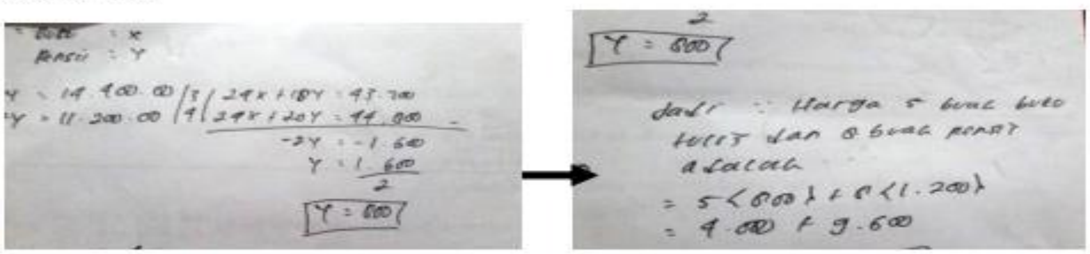
Mathematical errors provide valuable evidence of students' misconceptions and problem-solving difficulties, supporting data-driven instructional decision-making. These errors may be conceptual, procedural, computational, interpretive, applicational, or related to logical reasoning (Radatz, 1979; Movshovitz-Hadar et al., 1987). Identifying such patterns enables teachers to diagnose learning gaps and select appropriate instructional responses. Conceptual errors reflect inadequate understanding of mathematical ideas (Skemp, 1976), while procedural and computational errors involve difficulties in applying procedures and numerical operations. Interpretation, application, and logical reasoning errors relate to difficulties in understanding mathematical information, transferring knowledge to new contexts, and constructing valid mathematical arguments. Systematic analysis of these errors can therefore inform targeted instructional interventions.

2.2.1 Conceptual Errors

Conceptual errors occur when students have an inadequate or incorrect understanding of mathematical concepts, principles, or relationships. Such errors often arise when learners rely on memorized rules without understanding the underlying mathematical meaning, resulting in persistent misconceptions and difficulties in problem-solving. Conceptual understanding therefore requires learners to understand not only what mathematical procedures to apply but also why they are appropriate (Skemp, 1976).

PM08

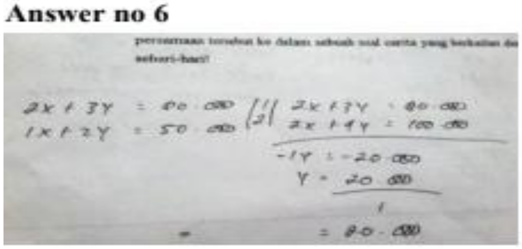
Answer no 4



Subject PM08 had errors in the procedure of entering the data given.

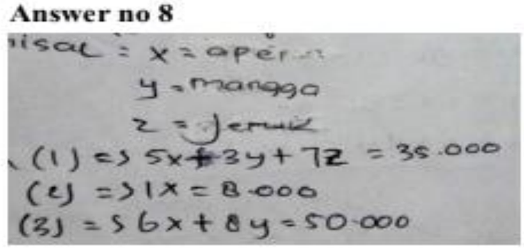
PM24

Answer no 6



Subject PM24 made an error in not continuing with the work.

Answer no 8



Subject PM24 made an error in placing the variable.

After analyzing students' responses, the study advanced to the third stage, which entailed classifying the types of errors found in students' solutions (WiNarso & Toheri, 2021). These errors were categorized according to their characteristics, and the contributing factors were examined. A primary category identified was conceptual error. Hiebert and Lefevre (1986) define conceptual errors as those resulting from insufficient understanding or improper application of the concepts necessary to solve a problem. Riccomini (2005) similarly notes that conceptual errors may involve choosing an incorrect formula, theorem, or definition; applying mathematical principles inconsistently with the problem's requirements; or misrepresenting the relevant mathematical concepts.

2.2.2 Procedural Errors

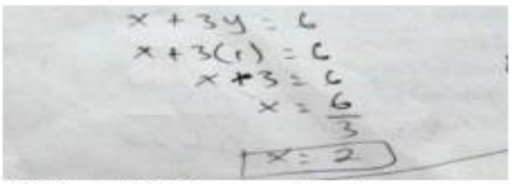
Procedural errors occur when students incorrectly apply mathematical procedures, algorithms, or sequences of operations despite having some understanding of the underlying concepts. Such errors may involve using incorrect formulas, omitting essential steps, or applying operations inaccurately. They often result from limited procedural fluency or reliance on memorized steps without sufficient understanding and practice (Hiebert & Carpenter, 1992).

2.2.3 Computational Errors

Computational errors involve mistakes in arithmetic calculations and numerical operations, such as addition, subtraction, multiplication, division, and simplification. They may result from weak numerical fluency, inattentiveness, or insufficient practice and can produce incorrect solutions even when students understand the underlying mathematical concepts and procedures (Van de Walle et al., 2019; Winarso & Toheri, 2021).

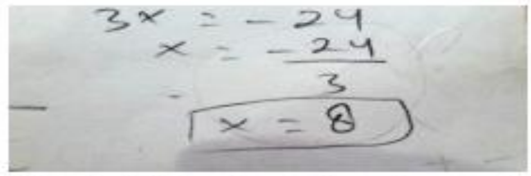
PM04

Answer no 1



Subject PM04 encountered an error on the use of the number operation sign, and this was due to the inability of the subject to solve the problem.

Answer no 3



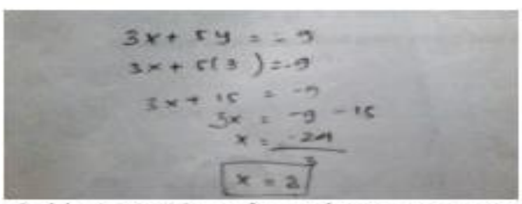
Subject PM04 also performed procedural errors in terms of the division of positive and negative numbers.

2.2.4 Interpretation Errors

Interpretation errors occur when students misinterpret mathematical language, symbols, graphs, diagrams, tables, or problem statements. They are particularly common in word problems, where learners must translate verbal information into mathematical form. Misunderstanding key terms or failing to comprehend the problem can disrupt the problem-solving process before mathematical procedures are applied. Such errors are therefore closely associated with mathematical language and reading comprehension (Newman, 1977; Winarso & Toheri, 2021).

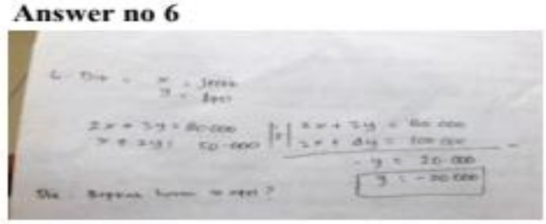
PM18

Answer no 3



Subject PM18 performed an error on number operation.

Answer no 6



Subject PM18 had two operations counting errors in integers.

2.2.5 Application Errors

Application errors occur when students fail to apply appropriate mathematical concepts or procedures to unfamiliar or real-life situations. These errors may arise when learners select inappropriate methods, struggle to transfer prior knowledge, or fail to connect mathematical concepts to new contexts. Effective problem-solving therefore requires identifying and applying relevant concepts and strategies to a given problem (Schoenfeld, 1985).

2.2.6 Logical Reasoning Errors

Logical reasoning errors occur when students draw invalid conclusions, make incorrect generalizations, or use faulty mathematical arguments. They are particularly relevant in areas such as algebra, geometry, and mathematical proofs, where learners must justify their solutions logically. Effective mathematical problem-solving requires systematic reasoning and careful evaluation of the steps used to reach a solution (Pólya, 1957).

3. Methodology

3.1 Research Design

The study employed a mixed-methods research design, integrating quantitative and qualitative approaches to examine data-driven instructional practices, teacher capacity, institutional support, and student achievement in mathematics. The quantitative component generated descriptive and inferential evidence on the study variables, while the qualitative component provided complementary insights into participants' experiences and perceptions. The integration of both approaches enabled a more comprehensive understanding of the implementation of data-driven instructional practices in public secondary schools.

3.2 Sample and Sampling Procedures

The study targeted 763 respondents, comprising mathematics teachers, students, head teachers, and sector education officers from 33 public secondary schools in Nyarugenge District, Rwanda. A sample of 263 participants was selected using stratified and simple random sampling techniques. Stratification ensured representation of the different categories of respondents, while simple random sampling provided eligible participants with an opportunity to be selected for the study.

3.3 Data Collection Tools

Instrument validity was established through expert review, while reliability was assessed using Cronbach's alpha. The overall reliability coefficients were 0.84 and 0.87 for the teacher and student questionnaires, respectively. At the construct level, Cronbach's alpha coefficients were 0.756 for Data Skills, 0.716 for Institutional Support, and 0.725 for Student Achievement in Mathematical Concepts, indicating acceptable internal consistency.

3.4 Data Collection Procedures

Following the necessary institutional and ethical approvals, permission to conduct the study was obtained from the relevant education authorities and participating schools. The researcher coordinated with school administrators to identify eligible participants and arrange appropriate data-collection schedules. Questionnaires were administered to the selected respondents, while semi-structured interviews were conducted with the relevant participants. For the quasi-experimental component, data were collected from intact classes to minimize disruption to normal school activities. Completed instruments were checked for completeness and prepared for analysis.

3.5 Data Analysis

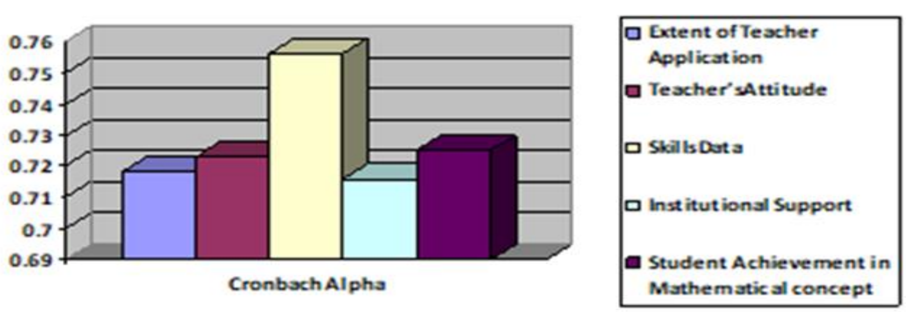
Quantitative data were analyzed using descriptive and inferential statistics. Frequencies, percentages, means, and standard deviations were used to summarize respondents' characteristics and responses to the study variables. Inferential analysis was conducted to examine the statistical relationships and differences relevant to the study objectives and hypotheses. Qualitative data obtained through semi-structured interviews were analyzed thematically to identify recurring patterns and themes that complemented the quantitative findings. Results were presented using tables and narrative interpretations.

3.6 Ethical Considerations

Ethical approval and relevant research authorization were obtained from Masinde Muliro University of Science and Technology and the National Commission for Science, Technology and Innovation (NACOSTI), together with permission from the relevant education authorities and participating schools in Nyarugenge District. Participants were informed about the purpose and procedures of the study before participation. Adult participants provided informed consent, while parental or guardian consent was obtained for participating in minors through the appropriate school procedures. Participation was voluntary, and participants' anonymity, confidentiality, and privacy were maintained throughout the research process. The study was conducted in intact classes to minimize disruption to normal school activities. All sources were appropriately acknowledged, and the findings were reported accurately and transparently without fabrication, falsification, or misrepresentation.

4.Results and Discussion

4.1 Reliability Test Results



To assess the internal consistency of the research instruments, we computed Cronbach's alpha coefficients. Following Adriani et al. (2020), an alpha coefficient of 0.70 or above was considered indicative of acceptable reliability. All constructs met this criterion. Data Skills, which measured teachers' knowledge and skills in data-driven instructional practices, recorded a Cronbach's alpha of 0.756, while Institutional Support yielded 0.716. Student Achievement in Mathematical Concepts, the dependent variable across the study objectives, recorded an alpha coefficient of 0.725. These coefficients demonstrate acceptable internal consistency, confirming that the instruments were sufficiently reliable for subsequent statistical analysis.

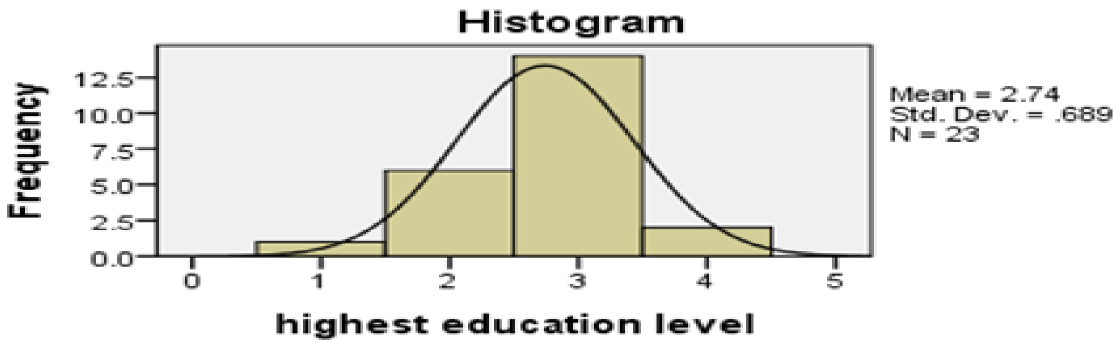
4.2 Education Level

Table 1: Respondents' Educational Qualifications

		Frequency	Percent
Valid	Certificate	1	4.3
	Diploma	6	26.1
	Bachelor's degree	14	60.9
	Master's degree	2	8.7
	Total	23	100.0

Note. Field Data, (2026)

The findings indicate that most mathematics teachers held a Bachelor's degree (60.9%, n = 14), followed by a Diploma (26.1%, n = 6). Teachers with a Master's degree accounted for 8.7% (n = 2), while Certificate holders represented 4.3% (n = 1). Overall, the findings show that most respondents had undergraduate-level qualifications, while only a small proportion had postgraduate qualifications. This variation in educational qualifications may reflect differences in teachers' professional preparation and capacity to engage with data-driven instructional practices.



4.3 Teachers' Skills in Data Use

Table 2: Teachers' Knowledge and Skills in Data Use

Skills in Data Use	5	4	3	2	1	M	S.D
I can interpret data from assessments to understand student progress.	10(43.5%)	9(39.1%)	2(8.7%)	2(8.7%)	0	4.17	.937
I know how to create basic data summaries (e.g., averages, charts).	12(52.2%)	7(30.4%)	2(8.7%)	2(8.7%)	0	4.26	.964
I can use data analysis tools (like Excel) to inform instruction.	10(43.5%)	12(52.2%)	1(4.3%)	0	0	4.39	.583
I can identify key trends from data reports.	13(56.5%)	9(39.1%)	1(4.3%)	0	0	4.52	.593
I understand how to use data to differentiate instruction.	14(60.9%)	6(26.1%)	3(13.0%)	0	0	4.48	.730

Note. SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree; M = Mean. Responses were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Field data (2026).

Teachers reported generally high levels of perceived competence in using data for instructional purposes, with mean scores ranging from 4.17 to 4.52. The highest-rated competency was identifying key trends from data reports (M = 4.52, SD = 0.593), followed by using data to differentiate instruction (M = 4.48, SD = 0.730) and using data-analysis tools such as Excel to inform instruction (M = 4.39, SD = 0.583). The comparatively lower ratings for interpreting assessment data (M = 4.17, SD = 0.937) and creating basic data summaries (M = 4.26, SD = 0.964) nevertheless remained above the scale midpoint. These findings indicate that teachers generally perceived themselves as competent in interpreting and applying educational data to support instructional decision-making. This pattern is consistent with literature emphasizing the importance of teachers' data literacy in effective data-driven instruction (Schildkamp, 2019; Datnow & Hubbard, 2020).

4.4 Institutional Support for Data-Driven Instruction

Table 3: Institutional Support for Data-Driven Mathematics Instruction

Institutional Support	SA, n (%)	A, n (%)	N, n (%)	D, n (%)	SD, n (%)	M	SD
The school trains teachers to use student data in teaching mathematics.	10 (43.5)	11 (47.8)	2 (8.7)	0 (0.0)*	0 (0.0)	4.35	0.647
I have the tools needed to analyze students' mathematics results.	7 (30.4)	8 (34.8)	7 (30.4)	1 (4.3)	0 (0.0)	3.91	0.900
The school provides feedback on how I use student data in lessons.	2 (8.7)	7 (30.4)	8 (34.8)	6 (26.1)	0 (0.0)	3.22	0.951
Teachers are given opportunities to share ideas on using student data in mathematics.	1 (4.3)	12 (52.2)	6 (26.1)	2 (8.7)	2 (8.7)	3.35	1.027
The school provides adequate resources to support data use in mathematics teaching.	0 (0.0)	9 (39.1)	13 (56.5)	1 (4.3)	0 (0.0)	3.35	0.573
Teachers who use student data in mathematics teaching are encouraged by the school.	9 (39.1)	14 (60.9)	0 (0.0)	0 (0.0)	0 (0.0)	**4.39***	0.490

Note. SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree; M = Mean. Responses were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Field data (2026).

The findings indicate varying levels of institutional support for data-driven mathematics instruction. Training on the use of student data received a high rating (M = 4.35, SD = 0.647), with 91.3% of teachers agreeing or strongly agreeing that their schools provided such training. Similarly, all respondents agreed or strongly agreed that teachers who used student data were encouraged by their schools. Access to data-analysis tools was also rated positively (M = 3.91, SD = 0.900), although 30.4% of respondents remained neutral. In contrast, opportunities for teachers to collaborate on data use (M = 3.35, SD = 1.027) and the provision of resources (M = 3.35, SD = 0.573) received comparatively moderate ratings. Feedback on teachers' use of student data recorded the lowest mean (M = 3.22, SD = 0.951), with only 39.1% agreeing or strongly agreeing. Overall, the findings suggest that institutional support was stronger in teacher training and encouragement but comparatively weaker in feedback, collaborative opportunities, and resource provision.

4.5 Teachers' Perceptions of Student Achievement in Mathematical Concepts

Table 4: Teachers' Perceptions of Student Achievement in Mathematical Concepts

Student Achievement in Mathematical Concepts	SA, n (%)	A, n (%)	N, n (%)	D, n (%)	SD, n (%)	M	SD
The mean mathematics test scores in this class reflect a strong understanding of mathematical concepts.	8 (34.8)	14 (60.9)	0 (0.0)	1 (4.3)	0 (0.0)	4.26	0.689
Students consistently perform well in mathematics tests and assessments.	14 (60.9)	7 (30.4)	0 (0.0)	2 (8.7)	0 (0.0)	4.43	0.896
Students demonstrate improvement in their mathematics test scores over time.	7 (30.4)	11 (47.8)	3 (13.0)	2 (8.7)	0 (0.0)	4.00	0.905
Students are able to correctly apply mathematical concepts during examinations.	12 (52.2)	10 (43.5)	1 (4.3)	0 (0.0)	0 (0.0)	4.48	0.593
Overall mathematics performance of students in this class is above average compared with previous terms.	12 (52.2)	10 (43.5)	1 (4.3)	0 (0.0)	0 (0.0)	**4.48***	**0.593***

Note. SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree; M = Mean. Responses were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Field data (2026).

Teachers generally reported positive perceptions of students' achievement in mathematical concepts, with mean scores ranging from 4.00 to 4.48. The highest-rated item concerned students' ability to correctly apply mathematical concepts during examinations (M = 4.48, SD = 0.593), with 95.7% of teachers agreeing or strongly agreeing. Similarly, 91.3% agreed or strongly agreed that students consistently performed well in mathematics tests and assessments (M = 4.43, SD = 0.896), while 95.7% perceived students' mean mathematics scores as reflecting a strong understanding of mathematical concepts (M = 4.26, SD = 0.689). The comparatively lowest rating concerned improvement in mathematics test scores over time (M = 4.00, SD = 0.905), although 78.2% of respondents still agreed or strongly agreed with the statement. Overall, the findings indicate that teachers generally perceived their students as demonstrating positive achievement in mathematics. However, because these findings are based on teachers' perceptions, they should be interpreted as self-reported assessments of student achievement rather than as direct measures of students' actual academic performance.

4.3.2 The observed outcome of your practices

Table 5: Teachers' Perceptions of the Outcomes of Data-Driven Instructional Practices

Item	SD	D	N	A	SA
Since using data-driven adjustments, my students' average scores on word problems have improved.	0 (0.0%)	0 (0.0%)	1 (4.3%)	5 (21.7%)	17 (73.9%)
The use of individualized feedback has reduced the number of students scoring below 50% on math tests.	0 (0.0%)	0 (0.0%)	0 (0.0%)	6 (26.1%)	17 (73.9%)
My students can now better explain how their test performance leads to a change in my teaching (e.g., re-teaching).	0 (0.0%)	1 (4.3%)	0 (0.0%)	6 (26.1%)	16 (69.6%)
Overall, the use of data to make instructional adjustments has significantly improved mathematical concept mastery in my class.	0 (0.0%)	0 (0.0%)	0 (0.0%)	3 (13.0%)	20 (87.0%)

Note. SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree. Field data (2026).

Mathematics teachers reported positive perceptions of the outcomes of data-driven instructional practices. Most teachers (95.6%) agreed or strongly agreed that data-driven adjustments had improved students' performance in word problems, while all respondents (100%) agreed or strongly agreed that individualized feedback had reduced the number of students scoring below 50% in mathematics tests. Similarly, 95.7% agreed or strongly agreed that students' test performance informed changes in their teaching, such as re-teaching, and all respondents (100%) perceived data-informed instructional adjustments as improving students' mastery of mathematical concepts. These findings indicate strong teacher perceptions of the value of data-driven practices in identifying learning gaps and informing instructional adjustments. This pattern is consistent with Data-Driven Decision-Making (DDDM) theory, which emphasizes the systematic use of student data to inform instructional decisions and support learning outcomes (Mandinach & Gummer, 2019.

4.4 Inferential Statistics

Table 6: **Descriptive Statistics for Skills in Data Use and Institutional Support**

Variable	N	M	SD	SE
Skills in Data Use	23	14.52	2.233	0.466
Institutional Support Structure	23	21.83	3.256	0.679

Note. M = mean; SD = standard deviation; SE = standard error.

Descriptive aggregate scores were obtained for Skills in Data Use (M = 14.52, SD = 2.233) and Institutional Support Structure (M = 21.83, SD = 3.256). However, because the constructs were measured using different numbers of questionnaire items, their aggregate means should not be directly compared to determine their relative importance or predictive strength. Therefore, further inferential analysis is required to determine the relationships between these variables and student achievement.

One-Sample Test

	Test Value = 3					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Skills in Data Use	24.741	22	.000	11.522	10.56	12.49
Institutional Support Structure	27.725	22	.000	18.826	17.42	20.23

The one-sample t-test compared teachers' mean scores for each variable against the neutral test value of 3 (the midpoint of the Likert scale). The results show that all four means are significantly greater than 3, with p-values less than 0.05 for every variable. The mean differences are large: 10.96 for Extent of Teacher's Application, 8.00 for Teachers' Attitude, 11.52 for Skills in Data Use, and 18.83 for Institutional Support Structure. The t-values range from 14.4 to 27.7, all with 22 degrees of freedom. This statistically confirms that, on average, mathematics teachers in Nyarugenge District rate themselves significantly above neutral on each of these four dimensions. This shows that, they report that they do apply data-driven practices, hold positive attitudes, possess strong skills and receive meaningful institutional support. These t-test results were evidence that all four constructs are present at levels significantly above the neutral point.

4.8 Students' Perceptions of Data-Driven Instructional Practices

Table 7: Students' Perceptions of Data-Driven Instructional Practices

Perceptions of Data-Driven Practices	SA, n (%)	A, n (%)	N, n (%)	D, n (%)	SD, n (%)	M	SD
My teacher uses test results to decide what we learn next.	104 (45.8)	69 (30.4)	35 (15.4)	17 (7.5)	2 (0.9)	4.13	0.990
My teacher explains how my test scores affect my progress.	51 (22.5)	114 (50.2)	52 (22.9)	17 (3.1)*	2 (1.3)*	3.89	0.829
My teacher uses data to give me feedback.	66 (29.1)	57 (25.1)	80 (35.2)	19 (8.4)	5 (2.2)	3.70	1.046
I feel that my teacher cares about my data results.	75 (33.0)	73 (32.2)	63 (27.8)	12 (5.3)	4 (1.8)	3.89	0.985
My teacher often checks how well I am doing in mathematics.	64 (28.2)	94 (41.4)	47 (20.7)	22 (9.7)	0 (0.0)	3.88	0.931
I get extra help when my data shows I need it.	19 (8.4)	71 (31.3)	121 (53.3)	16 (7.			

Note. SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree; M = Mean. Responses were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Field data (2026).

Students' perceptions revealed variations in the implementation of data-driven instructional practices. Teachers' use of test results to determine subsequent learning activities received the highest rating (M = 4.13, SD = 0.990), with 76.2% of students agreeing or strongly agreeing. Regular monitoring of students' mathematics performance was also positively perceived (M = 3.88, SD = 0.931), with 69.6% indicating agreement or strong agreement. Data-informed feedback received a comparatively lower rating (M = 3.70, SD = 1.046), while the provision of additional support when student data indicated a need recorded the lowest mean (M = 3.41, SD = 0.743), with only 39.7% agreeing or strongly agreeing and 53.3% remaining neutral. Overall, the findings suggest that assessment data were more consistently perceived as being used for general instructional planning and monitoring than for individualized support and remediation. This pattern is consistent with DDDM and TPACK perspectives, which emphasize the importance of teacher capacity and supportive institutional conditions in translating educational data into differentiated instructional action.

5. Conclusion and Recommendations

5.1 Conclusion

The study concludes that data-driven instructional practices contribute to mathematics teaching by supporting teachers' identification of learning needs and instructional planning. Mathematics teachers demonstrated competence in interpreting learner data; however, gaps remained in individualized feedback, continuous monitoring, and the practical application of data to differentiated instruction. Institutional support was particularly evident in professional development, although limitations remained in feedback mechanisms, collaborative opportunities, and resource provision. Effective data-driven mathematics instruction therefore requires the integration of teacher capacity, practical pedagogical application, technological competence, and sustained institutional support.

5.2 Recommendations

Based on the findings of the study, the following recommendations are proposed:

1. Strengthen teachers' capacity for practical data use. Professional development should integrate TPACK principles and emphasize the application of data to differentiate instruction, provide individualized feedback, and design targeted mathematics interventions.
2. Provide continuous school-based instructional support. Schools should establish coaching and mentoring mechanisms to help mathematics teachers translate data-use skills into effective classroom practices.
3. Strengthen institutional feedback mechanisms. School leaders should provide regular, constructive feedback on teachers' data-use practices through lesson observations, peer review, and other appropriate mechanisms.
4. Promote collaborative data-use practices. Schools should strengthen professional learning communities where mathematics teachers jointly analyze student data, share instructional strategies, and develop interventions for identified learning gaps.
5. Improve data-use resources and infrastructure. The Ministry of Education and Rwanda Basic Education Board (REB) should support schools with appropriate data-analysis tools, reliable internet connectivity, assessment materials, and other necessary resources.
6. Strengthen monitoring and targeted support. District education authorities should regularly monitor data-driven instructional practices and provide targeted support to schools facing limitations in resources, leadership, or teacher capacity.

5.3 Area of Further Research

Future studies should combine classroom observations with self-reported measures to examine the actual implementation of data-driven instructional practices. Further research should explore how digital assessment platforms, learning management systems, and data-analysis tools support student-progress monitoring and instructional decision-making. Comparative studies across STEM disciplines could also determine whether challenges in translating student data into individualized feedback vary across subject areas, thereby informing targeted professional development for data-driven instruction.

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