International Multidisciplinary Journal of Emerging Technologies and Applications (IMJETA)
Vol. 1, No. 1, pp. 151-162, July 2026
Received July 04, 2026; Revised July 06, 2026; Accepted July 28, 2026
Published July 31, 2026

Data Science and Machine Learning in Secondary Education: A Case Study of Barriers and Opportunities at Cambine Secondary School, Mozambique

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Abstract. This study examines the potential of Data Science (DS) and Machine Learning (ML) to transform teaching and learning at Cambine Secondary School, a rural institution in Inhambane Province, Mozambique, characterized by limited technological infrastructure. Using a concurrent mixed-methods case study design, data were collected through semi-structured interviews with two school directors and nine teachers, alongside structured questionnaires administered to sixty students and nine teachers, analyzed thematically and through descriptive and inferential statistics. The findings reveal substantial barriers, including unreliable or absent internet connectivity, a shortage of computers, near-total absence of virtual learning environments, and low teacher familiarity with DS/ML concepts, with only a quarter of teachers reporting that they understand them. Nevertheless, participants expressed strong interest: most students want to learn more about DS and ML, and most teachers believe such tools could support personalized learning. Inferential comparisons between the two groups showed significant differences in perceived internet adequacy and in familiarity with DS/ML concepts ($p < .05$), while perceptions of resource adequacy and optimism about the personalizing potential of these tools were broadly shared. The study concludes that, despite significant infrastructural and training gaps, a coordinated strategy combining infrastructure investment, continuous teacher training, curriculum integration, and public-private partnerships could enable DS and ML to meaningfully improve teaching quality and school management. These findings contribute to the broader debate on digital transformation in resource-constrained settings and offer practical recommendations aligned with Mozambique's national education strategy and international frameworks such as Sustainable Development Goal 4.

Keywords: Data Science; Machine Learning; Rural Education; Digital Transformation; Mozambique.

1. Introduction

Digital technologies, particularly Data Science and Machine Learning, are increasingly reshaping teaching and learning worldwide by enabling personalized instruction, predictive analysis of academic performance, and more efficient school management. In resource-constrained contexts such as rural Mozambique, however, the adoption of these technologies faces structural obstacles that are rarely examined empirically. This paper reports findings from a case study conducted at Cambine Secondary School, in Inhambane Province, Mozambique, an institution that reflects the infrastructural and pedagogical challenges common to many rural African schools.

The motivation for this study stems from direct professional experience within the school community, where persistent gaps were observed in technology use: inadequate infrastructure, absence of specialized technical training, and scarcity of pedagogical resources. These limitations restrict the transformative potential that Data Science and Machine Learning could otherwise offer to teaching and learning processes.

The central research question guiding this study is: to what extent can the application of Data Science and Machine Learning transform the teaching and learning process at Cambine Secondary School, considering its limitations and potentialities? To address this question, the study pursued the following specific objectives: (i) to investigate teachers' and students' perceptions of the impact of DS- and ML-based tools on teaching; (ii) to assess the technological infrastructure available at the school; (iii) to analyze the challenges faced by teachers and directors in adopting educational technologies; and (iv) to propose practical strategies for integrating DS and ML into the school's educational environment.

This article condenses the results of a broader mixed-methods dissertation study into a research paper suitable for wider dissemination. Section 2 reviews the theoretical framework; Section 3 describes the research design and methods; Section 4 presents and discusses the qualitative and quantitative findings; and Section 5 offers recommendations and concluding remarks.

2. Theoretical Framework

2.1. Foundations of Data Science and Machine Learning in Education

Data Science can be broadly understood as the interdisciplinary combination of statistics, computer science and domain expertise used to extract meaningful knowledge from data, while Machine Learning refers to algorithms capable of improving their performance on a task through experience, without being explicitly reprogrammed (Mitchell, 1997; Géron, 2019). Within education, both fields underpin what is commonly termed learning analytics: the measurement, collection and analysis of data about learners in order to understand and optimize learning and its environments (Baker & Siemens, 2014; Gasevic et al., 2015). Connectivist theory (Siemens, 2005) provides a complementary lens, arguing that in digitally networked societies learning increasingly depends on the ability to navigate, filter and connect distributed sources of information, a capability that DS and ML tools are well positioned to support. This expansion mirrors the broader growth of research on artificial intelligence applications in education worldwide (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019), and is consistent with UNESCO's own recognition that data-driven technologies can support the Sustainable Development Goals in education when deployed with adequate infrastructure and safeguards (Pedro, Subosa, Rivas, & Valverde, 2019).

2.2. Learning Management Platforms and Personalization

Virtual learning environments such as Moodle and Google Classroom incorporate DS/ML-driven functionalities to track learner progress, provide automated feedback, and adapt content to individual needs (Sarker et al., 2020). Evidence from other developing-country contexts suggests that adoption of such platforms can improve engagement and outcomes when properly supported by infrastructure and teacher training, but that the absence of either factor significantly undermines their potential (Selwyn, 2016). Beyond individual platforms, Luckin, Holmes, Griffiths, and Forcier (2016) argue that AI-driven tools can support adaptive, personalized learning pathways at scale, whereas Williamson (2017) cautions that the growing reliance on big data and learning analytics in schools also raises questions of data governance and surveillance, concerns that are particularly salient where regulatory and technical capacity remain limited.

2.3. Pedagogical Approaches: From Traditional to Active Learning

Traditional, teacher-centered instruction contrasts with active pedagogical approaches that position the learner as a co-constructor of knowledge, consistent with socio-constructivist theory (Vygotsky, 1978). Meta-analytic evidence indicates that active learning approaches increase student performance in science and engineering disciplines relative to traditional lecturing (Freeman et al., 2014). DS and ML tools can facilitate this pedagogical shift by enabling differentiated instruction based on real-time evidence of student progress, although this requires teachers to move beyond purely transmissive teaching models.

2.4. Regulatory and Policy Frameworks

The integration of Information and Communication Technologies in Mozambican education is supported by a robust, though unevenly implemented, policy framework, including the National Education System Law and the Strategic Education Plan 2020-2029, both of which identify digital inclusion as a strategic priority (Assembleia da República, 2018; MINEDH, 2020). These national instruments align with continental and global commitments such as the African Union's Agenda 2063 and Continental Education Strategy for Africa, and with Sustainable Development Goal 4 and the Education 2030 Incheon Framework for

Action (African Union, 2015, 2016; UNESCO, 2015a, 2015b). Despite this normative alignment, the literature suggests that policy intent alone is insufficient without accompanying investment in infrastructure and teacher capacity, a gap that this study examines empirically at the school level.

At a broader level, artificial intelligence and data-driven technologies have been shown to meaningfully advance the Sustainable Development Goals, including SDG 4, provided that investment in infrastructure and human capital keeps pace with technological ambition (Vinuesa et al., 2020; Mhlanga, 2021). This mirrors earlier continent-wide assessments of ICT in African education systems, which identified persistent gaps in connectivity, teacher training and cost-effective implementation (Trucano, 2005; Farrell, Isaacs, & Trucano, 2007). Hilbert (2016) further notes that the promise of data-driven decision-making in developing countries is often constrained by a "data divide" rooted in structural shortages of infrastructure and skilled personnel, a pattern consistent with the digital-teacher competency gaps documented by Ally (2019).

3. Materials and Methods

3.1. Research Design

This study adopted a concurrent mixed-methods case study design (Creswell & Clark, 2018; Yin, 2016), combining qualitative and quantitative techniques to provide a comprehensive understanding of DS/ML adoption at Cambine Secondary School. The case study approach was considered appropriate because it allows the exploration of a contemporary phenomenon within its real-life context, particularly where the boundaries between the phenomenon and its context are not clearly evident (Yin, 2016).

3.2. Participants and Sampling

Participants were selected through purposive sampling (Patton, 2015), targeting individuals with direct relevance to the research questions: teachers, students, and school directors. Table 1 summarizes the final achieved sample.

Table 1. Final study sample

Participant group	Instrument	n
Students	Questionnaire	60
Teachers	Questionnaire	9
Teachers	Semi-structured interview	9
School directors	Semi-structured interview	2

In total, 69 questionnaires and 11 interviews were completed. Prior to full data collection, a pilot test was conducted with five participants (two teachers, two students, and one director) to validate the clarity, length and structure of the instruments; adjustments were made based on the feedback received.

3.3. Data Collection Instruments

Semi-structured interviews were conducted with the school directors and teachers, following an interview guide covering infrastructure, current technology use, and perceived challenges and opportunities for DS/ML integration (Kvale & Brinkmann, 2015). Structured questionnaires with closed-ended items were administered to students and teachers to capture the frequency of technology use, perceived impact, and satisfaction with available tools (Bryman, 2016). Combining both instruments enabled data triangulation, strengthening the validity of the findings (Creswell & Clark, 2018).

3.4. Data Analysis

Qualitative data from the interviews were examined using thematic analysis (Braun & Clarke, 2006), which allowed recurrent patterns regarding infrastructure, training needs and the perceived potential of DS/ML to be identified across directors' and teachers' accounts. Quantitative data from the questionnaires were first examined descriptively, through frequencies and percentages, to characterize technology access, use and perceptions among students and teachers. To move beyond purely descriptive statistics, as recommended by Field (2018), selected indicators were also subjected to inferential analysis. One-sample chi-square goodness-of-fit tests (Fisher, 1922) were used to determine whether the observed distribution of responses for key indicators departed significantly from an equal (50/50) distribution.

In addition, Fisher's exact test, appropriate given the small size of the teacher sample ($n = 9$), was used to test for significant differences between students and teachers on four thematically comparable indicators: perceived adequacy of internet access, familiarity with DS/ML concepts, perceived adequacy of technological resources, and belief in the positive or personalizing impact of DS/ML tools. Counts for these tests were derived from the reported percentages and known sample sizes ($n = 60$ students; $n = 9$ teachers), rounded to the nearest whole respondent. All statistical tests were conducted with a significance threshold of $\alpha = .05$.

4. Results and Discussion

4.1. Qualitative Findings

Interviews with school directors revealed consistent recognition that current infrastructure, particularly unreliable electrical installations and an insufficient number of computers, is inadequate to support the integration of DS/ML-based tools. Neither director reported use of a formal virtual learning environment; WhatsApp was identified as the school's principal digital communication tool, but its effectiveness was described as limited by the absence of technical training and educational functionality. Although a written strategic plan for technology integration exists, both directors confirmed it had not been implemented due to a lack of financial resources. Directors nonetheless expressed strong interest in pursuing teacher training and infrastructure partnerships as first steps, and anticipated that DS/ML adoption could improve both academic monitoring and administrative management.

Interviews with the nine teachers echoed similar themes. All reported relying exclusively on WhatsApp for classroom-related communication, with no other digital platform in regular use. Perceptions of technology's impact on student performance were mixed, ranging from moderate to positive, but were consistently qualified by infrastructural limitations, particularly unstable or absent internet access. All nine teachers agreed that DS/ML tools could improve teaching, citing benefits such as tracking student progress, personalizing instruction, and optimizing the use of instructional resources, but stressed that prior training would be essential, since the large majority had never received specific instruction in these areas. Reported barriers included limited internet access, insufficient devices, and initial resistance from both students and teachers to unfamiliar tools.

4.2. Quantitative Findings

Table 2 summarizes selected indicators from the student questionnaire. A large majority of students rely on smartphones as their primary study device, compared with far fewer using computers or tablets, underscoring the centrality of mobile access in this context. Only half of the students reported consistent internet access, and most considered the technical support provided by the school inadequate. Despite these constraints, most students believed that technological tools have a positive impact on learning, were already familiar with the concept of Data Science, supported introducing DS/ML content into the school curriculum, and expressed interest in learning more about these topics.

Table 2. Selected indicators from the student questionnaire (n = 60)

Indicator	%
Use a smartphone as the main device for studying	90
Have consistent internet access	50
Consider the school's technical support inadequate	70
Believe technology has a positive impact on learning	80
Have never used a virtual learning environment	50
Are familiar with the concept of Data Science	70
Support introducing Data Science / Machine Learning content in the curriculum	90
Are willing to learn more about Data Science and Machine Learning	85

Table 3 presents selected indicators from the teacher questionnaire. Very few teachers reported currently using DS/ML-based tools in their pedagogical practice, and most considered the school's technological resources inadequate. All teachers confirmed that the school lacks internet connectivity, and the large majority rated available connectivity, where accessible elsewhere, as insufficient for teaching purposes. Most teachers had never attended training on educational technologies, and only a quarter reported understanding basic DS/ML concepts. Nevertheless, most teachers believed DS/ML tools could support the personalization of student learning.

Table 3. Selected indicators from the teacher questionnaire (n = 9)

Indicator	%
Currently use Data Science / Machine Learning tools in teaching practice	10
Consider the school's technological resources inadequate	85
Report the school has no internet connectivity	100
Consider available internet access inadequate for teaching	90
Have never attended training on educational technologies	65
Understand basic Data Science / Machine Learning concepts	25
Believe Data Science / Machine Learning tools could personalize learning	90

4.2.3. Statistical Analysis of Group Differences

To complement the descriptive percentages reported above, one-sample chi-square goodness-of-fit tests were used to verify whether key response patterns departed significantly from an equal (50/50) split. As shown in Table 4, students' reliance on smartphones as their main study device, their willingness to learn more about DS/ML, their support for including DS/ML content in the curriculum, and teachers' near-unanimous reports of the absence of school internet connectivity were all significantly different from chance ($p < .05$ in all cases but one), confirming that these are robust patterns rather than artifacts of small-sample variability.

Table 4. Chi-square goodness-of-fit tests for selected indicators (H_0: 50/50 distribution).

Indicator	Group	n	%	χ^2	*p*
Use smartphone as main study device	Students	60	90	38.40	< .001
Familiar with the concept of Data Science	Students	60	70	9.60	.002
Willing to learn more about DS/ML	Students	60	85	29.40	< .001
Support DS/ML content in the curriculum	Students	60	90	38.40	< .001
Report school has no internet connectivity	Teachers	9	100	9.00	.003
Consider internet access inadequate for teaching	Teachers	9	90	5.44	.020

Understand basic DS/ML concepts	Teachers	9	25	2.78	.096
Believe DS/ML tools can personalize learning	Teachers	9	90	5.44	.020

To examine whether students and teachers differ systematically in their perceptions, Fisher's exact test — appropriate given the small teacher sample — was applied to four thematically paired indicators (Table 5). Students were significantly more likely than teachers to consider their internet access adequate (50% vs. 11%, p = .035) and significantly more likely to report familiarity with DS/ML concepts (70% vs. 22%, p = .009).

In contrast, no significant difference was found between the two groups in their perception that available technological resources are inadequate (70% vs. 89%, p = .427) or in their belief that DS/ML tools can have a positive or personalizing effect on learning (80% vs. 89%, p = 1.000), suggesting that concern about resource adequacy and optimism about the pedagogical potential of these tools are broadly shared across the school community, whereas actual exposure to connectivity and to DS/ML concepts is markedly more limited among teachers than among students.

Table 5. Fisher's exact test comparing students and teachers on paired indicators.

Indicator	Students % (n=60)	Teachers % (n=9)	OR	p
Consider internet access adequate	50.0	11.1	8.00	.035
Familiar with / understand DS/ML concepts	70.0	22.2	8.17	.009
Consider tech. resources/support inadequate	70.0	88.9	0.29	.427
Believe DS/ML has a positive/personalizing impact	80.0	88.9	0.50	1.000

These results should be interpreted with caution given the small teacher sample (n = 9), which limits statistical power and widens the confidence intervals around teacher proportions; they are reported as indicative rather than conclusive evidence of group differences, and are intended to complement, rather than replace, the descriptive and qualitative findings presented above.

4.3. Discussion

Taken together, the qualitative and quantitative findings point to a coherent pattern: strong stakeholder interest and perceived pedagogical value coexisting with severe infrastructural and training deficits. This pattern is consistent with the broader literature on educational technology adoption in resource-constrained settings, which emphasizes that technological potential cannot be realized without parallel investment in connectivity, hardware, and teacher capacity (Selwyn, 2016). The near-universal reliance on WhatsApp as the sole digital tool, despite its limited pedagogical functionality, illustrates how, in the absence of dedicated virtual learning environments, informal platforms fill an infrastructural vacuum, a finding that echoes concerns raised in the learning analytics literature about tools not originally designed for structured educational data collection (Baker & Siemens, 2014).

The gap between high interest and comparatively low actual competence in DS/ML suggests that awareness-raising alone is insufficient and that structured, sustained training programs are required, consistent with theoretical arguments for active, scaffolded approaches to skill development (Vygotsky, 1978; Freeman et al., 2014). These findings resonate directly with Mozambique's own policy commitments, since both the Strategic Education Plan 2020-2029 and the National Education System Law foreground digital inclusion (MINEDH, 2020; Assembleia da República, 2018), as well as with continental and global commitments under the Continental Education Strategy for Africa, Agenda 2063, and Sustainable Development Goal 4 (African Union, 2015, 2016; UNESCO, 2015a, 2015b). The persistent implementation gap identified in this case study suggests that translating policy intent into practice at the school level requires more targeted, resourced, and locally adapted action plans than currently exist.

5. Recommendations

Based on the findings, the following measures are proposed to support the integration of Data Science and Machine Learning at Cambine Secondary School and comparable institutions:

- Infrastructure investment: expand high-speed internet access, provide computers and modern devices in classrooms, and establish well-equipped computer laboratories.
- Continuous teacher training: implement regular capacity-building programs on Data Science and Machine Learning, ranging from foundational concepts to classroom applications, complemented by practical guides and peer-learning workshops.
- Curriculum integration: incorporate Data Science and Machine Learning modules or cross-curricular activities that build relevant competencies among students.
- Pedagogical innovation: support pilot projects that apply Machine-Learning-based personalization and use analytics to inform data-driven pedagogical interventions.
- Strategic partnerships: establish collaborations with universities, technology companies, and national or international organizations to secure equipment, funding, and technical expertise.
- Digital equity: ensure that infrastructure and training initiatives explicitly prioritize the most vulnerable students and teachers, avoiding the reproduction of existing inequalities.

6. Conclusion

This study examined how Data Science and Machine Learning could transform teaching and learning at Cambine Secondary School, and found that, despite considerable barriers, this transformation is both desirable and feasible under the right conditions. Infrastructural limitations, unreliable electricity, insufficient computers, and largely absent internet connectivity, together with limited teacher training, currently constrain the effective use of these technologies. At the same time, students and teachers alike expressed considerable enthusiasm and recognized the pedagogical value of Data Science and Machine Learning, indicating a receptive environment for change.

Limitations of the Study. This study has several limitations that should be acknowledged. First, the small size of the teacher and director samples (nine and two participants, respectively) limits the statistical power of the inferential analyses and the generalizability of teacher-level findings; results for this group should be interpreted as indicative rather than conclusive. Second, the case-study design, focused on a single rural school, means that findings reflect the specific infrastructural and socio-economic conditions of Cambine Secondary School and cannot be generalized to other contexts without caution. Third, data collection relied on self-reported perceptions, which may be subject to social desirability bias, particularly in interviews conducted with school directors. Finally, the cross-sectional design captures perceptions and conditions at a single point in time and does not allow change to be assessed following any future intervention. Future research should extend this work to a larger and more diverse sample of schools, incorporate longitudinal designs to track change following training or infrastructure investment, and complement self-reported data with observational or administrative measures of technology use.

Addressing these barriers will require coordinated investment in infrastructure, sustained and practice-oriented teacher training, deliberate curriculum integration, and strategic partnerships between the school, government, universities, and technology providers. These measures align closely with Mozambique's national education policies and with continental and global education agendas, suggesting that local action at Cambine could both benefit directly from, and contribute evidence to, these broader frameworks. Notwithstanding the limitations noted above, the findings offer a transferable model for how resource-constrained schools might approach the strategic, phased adoption of Data Science and Machine Learning to build a more inclusive, personalized, and effective educational system.

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