ISSN: 2708-4841(Print), 2708-7042 (Online)

Volume: 7, Issue: 10
Page: 1 -14
YEAR: 2026

Commonwealth Journal of Academic Research (CJAR.EU)

Predicting Mathematics Achievement through Learning Analytics and Classroom Engagement among Senior Secondary School Students in Nigeria

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Abstract:

Persistent underachievement in secondary school mathematics in Nigeria has drawn attention to data-informed teaching practices and to student engagement as possible levers for improvement, yet evidence on how these factors predict achievement in Nigerian classrooms remains limited. This study examined the extent to which learning analytics and classroom engagement predict mathematics achievement among senior secondary school students. A descriptive survey of the correlational type was conducted with 100 senior secondary school students selected from public secondary schools through multistage sampling. Data were collected using the Learning Analytics, Classroom Engagement and Mathematics Achievement Questionnaire (LACEMAQ; Cronbach's α = .84 for learning analytics, .87 for classroom engagement and .86 overall), while mathematics achievement scores were obtained from school assessment records. Data were analysed using descriptive statistics and simple linear regression at the .05 level of significance. Students reported high exposure to learning analytics practices (grand mean = 3.45 on a 4-point scale) and high classroom engagement (grand mean = 3.43). Learning analytics did not significantly predict mathematics achievement (β = .086, t = 0.850, p = .398; R^2 = .007; $F(1, 98)$ = 0.722). Classroom engagement significantly predicted mathematics achievement (β = .268, t = 2.750, p = .007; R^2 = .072; $F(1, 98)$ = 7.561), accounting for 7.2% of the variance. Classroom engagement, but not the current form of learning analytics practice, is a significant predictor of mathematics achievement. Schools should prioritise learner-centred strategies that raise active participation, while investing in the infrastructure and teacher data literacy needed for learning analytics to move beyond record-keeping to actionable, personalised intervention.

Keywords: learning analytics, classroom engagement, mathematics

CJAR
Accepted 20 October 2026
Published 30 October 2026
DOI: 10.5281/zenodo.24218259

achievement, secondary education, data-informed teaching, Nigeria,

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1. Introduction

Mathematics occupies a central place in secondary education because it underpins science, technology, engineering, economics and everyday quantitative reasoning. Proficiency in the subject equips learners with the logical reasoning, problem-solving and decision-making competencies that are increasingly demanded in a knowledge-driven economy. In Nigeria, Mathematics is compulsory at the senior secondary level and a credit pass is a prerequisite for admission into most tertiary programmes. Despite repeated curriculum reforms and instructional innovations, students' performance in the subject remains a recurring concern, and the chief examiners' reports of the West African Examinations Council continue to document weaknesses in candidates' conceptual understanding, problem solving and application of mathematical principles (West African Examinations Council [WAEC], 2023).

Mathematics achievement, the criterion variable in this study, refers to the level of competence students demonstrate in mathematics as reflected in classroom tests, continuous assessment and external examinations. It captures mastery of concepts, computational fluency and the capacity to apply mathematical knowledge to unfamiliar problems. Achievement is shaped by an interplay of instructional, psychological, technological and contextual factors, and a long tradition of research has shown that the quality of feedback students receive and the extent of their active involvement in learning are among the most consequential of these factors (Black & Wiliam, 1998; Hattie & Timperley, 2007). Nigerian research has similarly linked mathematics outcomes to the instructional approach adopted, with learner-centred methods such as problem-based learning supporting achievement and retention among both male and female students (Ajai & Imoko, 2015).

Learning analytics is the first of two predictor variables examined in this study. It is commonly defined as the measurement, collection, analysis and reporting of data about learners and their contexts for the purpose of understanding and optimising learning and the environments in which it occurs (Ferguson, 2012; Siemens & Baker, 2012). In practice, learning analytics enables teachers to monitor attendance, assignment completion, test performance and participation, to identify learners at risk of underachievement and to intervene before learning gaps widen. Reviews of the field show that learning analytics has been widely used to predict performance and to inform student support, although robust evidence that it improves learning outcomes remains thinner than its promise suggests (Ifenthaler & Yau, 2020; Viberg et al., 2018). In secondary schools with limited digital infrastructure, learning analytics frequently takes a low-technology form in which teachers use attendance registers, continuous assessment records and test scores to track progress and plan instruction.

Classroom engagement is the second predictor. It refers to the extent to which students invest behavioural, emotional and cognitive effort in classroom learning (Fredricks et al., 2004). Behaviourally engaged students attend, participate and complete tasks; emotionally engaged students show interest and enjoyment; and cognitively engaged students apply deliberate strategies and persist with difficult problems. Engagement is malleable and responsive to teachers' practices, which makes it an attractive target for intervention (Reeve & Cheon, 2021; Wang & Eccles, 2013), and a meta-analysis of 69 independent studies confirmed a moderately strong positive association between overall engagement and academic achievement (Lei et al., 2018).

The two predictors are conceptually complementary. Learning analytics supplies teachers with evidence on which to base instructional decisions, whereas engagement determines whether students take up the learning opportunities those decisions create. In many Nigerian

secondary schools, however, mathematics lessons remain predominantly teacher-centred, classes are large, and the use of digital learning systems is constrained by infrastructure, connectivity and teacher preparation (Eze et al., 2018). Under these conditions it is unclear whether students' exposure to data-informed monitoring practices translates into higher achievement, or whether active engagement retains its predictive value. Most empirical work on learning analytics has been conducted in higher education and in technology-rich systems (Sønderlund et al., 2019; Viberg et al., 2018), leaving secondary schools in sub-Saharan Africa underrepresented in the evidence base.

Against this background, the present study examined the extent to which learning analytics and classroom engagement predict mathematics achievement among senior secondary school students. Specifically, the study sought to (a) determine the predictive influence of learning analytics on mathematics achievement, and (b) examine the predictive influence of classroom engagement on mathematics achievement. The findings are intended to inform teachers, school administrators, curriculum planners and policymakers seeking evidence-based strategies for improving mathematics teaching and learning.

2. Literature Review

2.1 Learning Analytics and Academic Achievement

The rationale for learning analytics rests on the well-established finding that timely and specific feedback is among the most powerful influences on learning (Hattie & Timperley, 2007). Learning analytics extends this principle by systematising the evidence on which feedback and instructional adjustment are based. Early syntheses described a rapidly expanding field concerned mainly with predicting performance, detecting at-risk learners and modelling student behaviour from digital traces (Papamitsiou & Economides, 2014). Gašević et al. (2015) cautioned, however, that analytics are useful only insofar as they are grounded in learning theory and connected to pedagogical action; counts of submissions or attendance do not, by themselves, improve learning.

Empirical evidence on learning outcomes is mixed. In a large distance-learning university, Herodotou et al. (2019) found that students of teachers who made regular use of a predictive analytics dashboard and intervened with flagged learners performed significantly better than students taught by the same teachers in an earlier course presentation without the tool. Conversely, systematic reviews have reported that most learning analytics studies focus on prediction rather than intervention, and that evidence of improved learning outcomes is limited and inconsistent (Sønderlund et al., 2019; Viberg et al., 2018). A review of learning analytics dashboards reached a similar conclusion, noting that few dashboards were grounded in models of self-regulated learning and that their effects on learning were seldom rigorously evaluated (Matcha et al., 2020). Ifenthaler and Yau (2020) likewise concluded that learning analytics can support study success, but that its benefit depends on the quality of the interventions that follow the analysis.

The teacher's role appears decisive. Wise and Jung (2019) showed that instructors' use of analytics involves a sequence of asking questions, interpreting data, taking action and checking impact, and that the value of analytics is lost when any link in this chain is weak. In resource-constrained schools, the chain may be interrupted by inadequate infrastructure, limited data literacy and large classes. Studies of e-learning adoption in Nigeria have identified inadequate internet facilities, insufficient user training and user attitudes as major barriers to the full utilisation of educational technology (Eze et al., 2018). These conditions suggest that learning analytics practices in Nigerian secondary schools may be largely record-

based and may not yet reach the level of personalised intervention that drives achievement gains.

2.2 Classroom Engagement and Mathematics Achievement

Engagement is widely conceptualised as a multidimensional construct comprising behavioural, emotional and cognitive components (Fredricks et al., 2004). Early longitudinal work showed that teacher involvement, structure and autonomy support predict students' behavioural and emotional engagement, which in turn shapes teachers' responses to students, creating reciprocal cycles of engagement or disaffection (Skinner & Belmont, 1993). Wang and Eccles (2013) further demonstrated that students' perceptions of the school context influence their behavioural, emotional and cognitive engagement through motivational beliefs, and that the different dimensions of engagement relate differently to achievement.

The link between engagement and achievement is well supported. Lei et al. (2018) reported a moderately strong positive correlation between overall engagement and achievement across 69 studies involving 196,473 participants, with behavioural, emotional and cognitive engagement each correlating positively with achievement and with the strength of association moderated by reporting method, cultural values and gender. Teacher–student relationships also matter: Martin and Collie (2019) found that the more positive relationships high school students had with their teachers across subjects, the higher their engagement, whereas a predominance of negative relationships depressed engagement. Intervention evidence indicates that engagement can be raised deliberately; a synthesis of 51 autonomy-supportive teaching interventions, 38 of them randomised controlled trials, showed that teachers can learn autonomy-supportive practices and that these yield benefits for students' motivation, engagement and classroom climate (Reeve & Cheon, 2021).

In mathematics and science specifically, active learning has a demonstrable effect on performance. A meta-analysis of 225 studies in undergraduate science, technology, engineering and mathematics courses found that active learning raised examination performance and reduced failure rates relative to traditional lecturing (Freeman et al., 2014). Kahu and Nelson (2018) argued that engagement arises at the interface between the student and the educational context, shaped by self-efficacy, emotions, belonging and wellbeing, which helps explain why engagement often transmits the effect of teaching practices to outcomes. Technology can support engagement, but a systematic evidence map showed that this depends on how technology is integrated into pedagogy rather than on its mere presence (Bond et al., 2020).

2.3 Theoretical Framework

The study is anchored on self-determination theory (Ryan & Deci, 2000) and the feedback model of Hattie and Timperley (2007). Self-determination theory proposes that students are more intrinsically motivated and more fully engaged when classroom conditions satisfy their basic psychological needs for autonomy, competence and relatedness. Engagement is the observable expression of this motivation and is therefore expected to be a proximal predictor of achievement. The feedback model holds that feedback is effective when it helps learners answer three questions: where am I going, how am I going, and where to next. Learning analytics practices are a mechanism for generating this information; their effect on achievement is therefore expected to be indirect, operating through the instructional actions teachers take and the feedback students receive.

Within this framework, learning analytics and classroom engagement serve as predictor variables and mathematics achievement as the criterion variable. The framework implies that

classroom engagement should relate more directly to achievement, whereas the contribution of learning analytics should depend on whether data are converted into actionable, personalised support.

2.4 Research Gap and Hypotheses

Although learning analytics and classroom engagement have each been studied extensively, few studies have examined both as predictors of mathematics achievement among secondary school students, and fewer still have done so in Nigeria, where learning analytics is at an early stage of adoption. The following null hypotheses were therefore tested at the .05 level of significance:

H_{01}: Learning analytics does not significantly predict mathematics achievement among secondary school students.

H_{02}: Classroom engagement does not significantly predict mathematics achievement among secondary school students.

3. Methodology

3.1 Research Design

A descriptive survey design of the correlational type was adopted. The design was appropriate because the study sought to establish the predictive relationships between naturally occurring variables, namely students' exposure to learning analytics practices, their classroom engagement and their mathematics achievement, without manipulating any of them.

3.2 Population and Sample

The population comprised all senior secondary school students in public secondary schools in the study area who were offering Mathematics as a compulsory subject during the period of the study. A multistage sampling procedure was used. First, participating public secondary schools were selected by simple random sampling. Second, the number of respondents drawn from each school was allocated in proportion to the school's student population. Third, students within each selected school were chosen by simple random sampling, yielding a total sample of 100 senior secondary school students.

3.3 Instrument

Data were collected with a researcher-designed instrument titled Learning Analytics, Classroom Engagement and Mathematics Achievement Questionnaire (LACEMAQ). Section A elicited demographic information, including gender, age, class level and school type. Section B contained two scales. The Learning Analytics Scale (10 items) measured students' experience of teachers' data-informed practices, such as monitoring of academic progress, use of test results to identify areas needing improvement, performance-based feedback, use of records for lesson planning, attendance monitoring and identification of students requiring additional support. The Classroom Engagement Scale (10 items) measured behavioural, emotional and cognitive involvement, including participation, questioning, attention, enjoyment of discussion, assignment completion, group work, sustained focus, contribution of ideas, motivation and effort. Items were rated on a four-point scale: Strongly Agree (4), Agree (3), Disagree (2) and Strongly Disagree (1), giving possible scale scores of 10 to 40. Mathematics achievement was measured using students' scores on the Mathematics Achievement Test obtained from standardised school assessment records.

3.4 Validity and Reliability

Face and content validity were established by experts in Mathematics Education, Educational Technology and Tests and Measurement, whose corrections on item clarity, relevance and coverage were incorporated into the final version. Reliability was established through a pilot

study with secondary school students who were not part of the main sample. Cronbach's alpha coefficients were .84 for the Learning Analytics Scale, .87 for the Classroom Engagement Scale and .86 for the entire instrument, all exceeding the conventional threshold of .70 for acceptable internal consistency (Tavakol & Dennick, 2011).

3.5 Data Collection and Ethical Considerations

Permission was obtained from the principals of the selected schools before data collection. The researcher, assisted by trained research assistants, administered the questionnaire in person during normal school hours. The purpose of the study was explained to participants, participation was voluntary, and respondents were assured that their responses would be treated confidentially and used solely for academic purposes. Completed questionnaires were retrieved on the spot, and all 100 were found usable for analysis.

3.6 Data Analysis

Item responses were summarised using frequencies, percentages, means and standard deviations. A criterion mean of 2.50 was adopted, such that item means of 2.50 and above indicated agreement. Each hypothesis was tested with simple linear regression at the .05 level of significance, with the scale score of the predictor regressed on mathematics achievement scores. Effect sizes were expressed as Cohen's f^2 and interpreted against the conventional benchmarks of .02 (small), .15 (medium) and .35 (large) (Cohen, 1988).

4. Results

4.1 Students' Reports of Learning Analytics Practices

Table 1 shows that all ten learning analytics items exceeded the criterion mean of 2.50, with a grand mean of 3.45. Agreement (Strongly Agree plus Agree) ranged from 92% to 100%, and no respondent selected Strongly Disagree. The highest-rated practices were teachers reviewing students' progress before introducing new topics (M = 3.61) and regular monitoring of academic progress (M = 3.56). The lowest-rated items were the motivating effect of performance monitoring (M = 3.24) and regular monitoring of attendance (M = 3.30), the latter attracting the highest level of disagreement (8%).

Table 1

Students' Responses on Learning Analytics Practices in Mathematics (N = 100)

S/N	Item	SA *n* (%)	A *n* (%)	D *n* (%)	SD *n* (%)	*M*	*SD*	Remark
1	My mathematics teacher regularly monitors my academic progress.	58 (58.0)	40 (40.0)	2 (2.0)	0 (0.0)	3.56	0.54	Agree
2	My mathematics test results are used to identify areas where I need improvement.	44 (44.0)	55 (55.0)	1 (1.0)	0 (0.0)	3.43	0.52	Agree
3	My teacher provides feedback based on my mathematics performance.	55 (55.0)	44 (44.0)	1 (1.0)	0 (0.0)	3.54	0.52	Agree
4	Records of my assignments help my teacher improve classroom instruction.	43 (43.0)	57 (57.0)	0 (0.0)	0 (0.0)	3.43	0.50	Agree
5	My teacher uses students' performance records to plan mathematics lessons.	53 (53.0)	47 (47.0)	0 (0.0)	0 (0.0)	3.53	0.50	Agree
6	My attendance in mathematics classes is monitored regularly.	38 (38.0)	54 (54.0)	8 (8.0)	0 (0.0)	3.30	0.61	Agree
7	My teacher identifies students	59	34	7 (7.0)	0 (0.0)	3.52	0.63	Agree

S/N	Item	SA *n* (%)	A *n* (%)	D *n* (%)	SD *n* (%)	*M*	*SD*	Remark
	who need extra academic support through assessment records.	(59.0)	(34.0)					
8	Continuous assessment results help improve my mathematics learning.	37 (37.0)	61 (61.0)	2 (2.0)	0 (0.0)	3.35	0.52	Agree
9	My teacher reviews my learning progress before introducing new mathematics topics.	63 (63.0)	35 (35.0)	2 (2.0)	0 (0.0)	3.61	0.53	Agree
10	Monitoring my academic performance motivates me to perform better in mathematics.	26 (26.0)	72 (72.0)	2 (2.0)	0 (0.0)	3.24	0.47	Agree
	Grand mean					3.45		Agree

Note. SA = Strongly Agree; A = Agree; D = Disagree; SD = Strongly Disagree. Item means and standard deviations were computed from response frequencies (SA = 4, A = 3, D = 2, SD = 1). Criterion mean = 2.50.

4.2 Students' Classroom Engagement in Mathematics

As shown in Table 2, all ten engagement items exceeded the criterion mean, with a grand mean of 3.43 and agreement ranging from 94% to 98%. Students rated most highly their readiness to ask questions when they did not understand a concept (M = 3.62) and their enjoyment of classroom discussions (M = 3.56). The lowest-rated item was active participation during mathematics lessons (M = 3.20), for which only 26% of students strongly agreed, followed by timely completion of assignments (M = 3.33). The consistently high ratings on both scales indicate limited variability in responses, a point that bears on the interpretation of the regression results.

Table 2

Students' Responses on Classroom Engagement in Mathematics (N = 100)

S/N	Item	SA *n* (%)	A *n* (%)	D *n* (%)	SD *n* (%)	*M*	*SD*	Remark
1	I actively participate during mathematics lessons.	26 (26.0)	68 (68.0)	6 (6.0)	0 (0.0)	3.20	0.53	Agree
2	I ask questions whenever I do not understand a mathematics concept.	68 (68.0)	26 (26.0)	6 (6.0)	0 (0.0)	3.62	0.60	Agree
3	I pay attention throughout mathematics lessons.	36 (36.0)	62 (62.0)	2 (2.0)	0 (0.0)	3.34	0.52	Agree
4	I enjoy participating in mathematics classroom discussions.	60 (60.0)	36 (36.0)	4 (4.0)	0 (0.0)	3.56	0.57	Agree
5	I complete my mathematics assignments on time.	35 (35.0)	63 (63.0)	2 (2.0)	0 (0.0)	3.33	0.51	Agree
6	I actively participate in group work during mathematics lessons.	48 (48.0)	47 (47.0)	5 (5.0)	0 (0.0)	3.43	0.59	Agree
7	I remain focused throughout mathematics classroom activities.	47 (47.0)	50 (50.0)	3 (3.0)	0 (0.0)	3.44	0.56	Agree
8	I contribute ideas during mathematics classroom discussions.	46 (46.0)	51 (51.0)	3 (3.0)	0 (0.0)	3.43	0.56	Agree
9	I feel motivated to participate in mathematics classroom activities.	51 (51.0)	47 (47.0)	2 (2.0)	0 (0.0)	3.49	0.54	Agree

S/N	Item	SA *n* (%)	A *n* (%)	D *n* (%)	SD *n* (%)	*M*	*SD*	Remark
10	I put extra effort into solving mathematics problems during class.	51 (51.0)	46 (46.0)	3 (3.0)	0 (0.0)	3.48	0.56	Agree
	Grand mean					3.43		Agree

Note. SA = Strongly Agree; A = Agree; D = Disagree; SD = Strongly Disagree. Item means and standard deviations were computed from response frequencies (SA = 4, A = 3, D = 2, SD = 1). Criterion mean = 2.50.

4.3 Testing of Hypotheses

The results of the simple linear regression analyses are presented in Table 3.

Table 3

Simple Linear Regression of Mathematics Achievement on Learning Analytics and Classroom Engagement

Model / predictor	*B*	*SE*	β	*t*	*P*	*R*	R^2	*F*(1, 98)
Model 1 (H_{01})								
Constant	28.132	6.593	-	4.267	< .001			
Learning analytics	0.162	0.191	.086	0.850	.398	.086	.007	0.722
Model 2 (H_{02})								
Constant	18.652	5.488	-	3.399	.001			
Classroom engagement	0.439	0.160	.268	2.750	.007	.268	.072	7.561

Note. Dependent variable = mathematics achievement score. *B* = unstandardised coefficient; *SE* = standard error; β = standardised coefficient. Model 1: $p = .398$ (not significant). Model 2: $p = .007$ (significant at .05).

Hypothesis 1. Learning analytics did not significantly predict mathematics achievement, $F(1, 98) = 0.722$, $p = .398$. The correlation between learning analytics and achievement was weak ($R = .086$), and learning analytics accounted for only 0.7% of the variance in mathematics achievement ($R^2 = .007$), leaving 99.3% attributable to variables outside the model. The corresponding effect size ($f^2 = .007$) fell below the threshold for a small effect. The null hypothesis was therefore not rejected. The fitted regression equation was: Mathematics achievement = 28.132 + 0.162 (Learning analytics).

Hypothesis 2. Classroom engagement significantly predicted mathematics achievement, $F(1, 98) = 7.561$, $p = .007$. Engagement was positively associated with achievement ($R = .268$, β = .268) and explained 7.2% of the variance in mathematics achievement ($R^2 = .072$), corresponding to a small-to-medium effect ($f^2 = .077$). Each one-point increase in the engagement score was associated with a 0.439-point increase in the achievement score. The null hypothesis was therefore rejected. The fitted regression equation was: Mathematics achievement = 18.652 + 0.439 (Classroom engagement).

5. Discussion

The first finding was that learning analytics did not significantly predict mathematics achievement, despite students reporting high exposure to data-informed practices, including progress monitoring, feedback based on student performance, and using student assessment records to plan lessons. This finding is in contrast to the evidence from technology-rich environments, where teachers' active use of predictive analytics and follow-up intervention was linked to improved student performance (Herodotou et al., 2019). However, it is in line with the findings of systematic reviews which show that research in learning analytics has focused on prediction and not intervention, and that learning outcomes are seldom demonstrated (Matcha et al., 2020; Sønderlund et al., 2019; Viberg et al., 2018).

There are three possible explanations. First, the learning analytics practices that were observed in this study were mostly record based, that is, attendance, test scores, and assignment records were kept. However, as Wise and Jung (2019) demonstrated, the usefulness of analytics is limited to teachers' ability to move beyond data interpretation to action and evaluating the effects of that action, which is what Gašević et al. (2015) had previously argued. Monitoring does not result in differentiated instruction or remediation and therefore, is unlikely to increase achievement. Second, the feedback model indicates that being monitored is not necessarily being given feedback on where to go next (Hattie & Timperley, 2007), and this is reflected in the relatively low rating on whether monitoring motivated students. Thirdly, infrastructural and training constraints reported in educational institutions in Nigeria (Eze et al., 2018) are likely to constrain the analytical depth that teachers can attain. Finally, the almost complete consensus on the learning analytics items limited the variation in scores, thereby statistically reducing the relationship between scores and achievement.

The second was that the extent to which students were engaged in the classroom had a significant and positive relationship with mathematics achievement. This is consistent with the meta-analytic findings of Lei et al. (2018) and the multidimensional view of engagement suggested by Fredricks et al. (2004) and Wang and Eccles (2013). It also aligns with the impact of active learning on performance in math-intensive courses (Freeman et al., 2014) and with evidence that positive teacher-student relationships help to keep students engaged (Martin & Collie, 2019). Questions, ideas, problem completion and attention help students process mathematical content, identify and correct misconceptions, and persevere with problems, leading to improved achievement.

The engagement effect was small (accounting for 7.2% of the variance). This is not surprising, as mathematics achievement is multiple determined by prior knowledge, teacher quality, home support and affective factors, and Lei et al. (2018) reported that this engagement–achievement relationship depends on how engagement is measured. The narrow spectrum of engagement scores in this sample likely also dampened the observed relationship and may indicate that the actual relationship is stronger. It is worth noting that the least rated engagement item related to active participation during lessons, which is in line with the largely teacher-centred nature of mathematics teaching in many classrooms in Nigeria. Autonomy-supportive teaching is learnable and can help students' engagement as it is the weakest dimension (Reeve & Cheon, 2021).

Overall, the results are consistent with the theory. In contrast, while learning analytics is a distal, teacher-side practice, engagement is a proximal, student-side influence on achievement, whose impact presumably relies on the learning analytics practice that it supports. This indicates that learning analytics could have an indirect effect on achievement, via engagement and feedback, which should be formally mediated.

6. Implications, Limitations and Directions for Future Research

Based on the findings, the mathematics teacher can apply strategies that can make students more active in learning, such as structured questioning, cooperative learning, peer tutoring, and problem-based learning (Ajai & Imoko, 2015), as well as autonomy-supportive practices that provide meaningful choices and explanations (Reeve & Cheon, 2021). Schools must shift from record keeping to actionable analytics, where teachers are trained to understand student data and to convert that data into specific feedback and remediation, to maximize achievement. Policy level investments are required in learning management systems,

connectivity and teachers' data literacy to provide the conditions for learning analytics to provide its desired benefits.

There are some caveats to be noted. The generalisability of the results of the one study area is limited due to the number of students sampled (100) as the study was able to detect medium effects but not small effects (a weak true effect of learning analytics cannot be ruled out). The predictor variables were assessed using students' self-report and the learning analytics was operationalised as students' perceptions of teachers' data practices instead of system-generated data. The ratings on both scales were very concentrated with a high mean, which limited the variance to be predicted. The cross-sectional design does not allow causal inference to be made and the two predictors were modelled separately, meaning that neither the joint nor relative contribution of the predictors was estimated. Achievement scores were taken from school records and may vary in standardisation from school to school.

Future research should involve larger, multi-state samples, integrate self-reporting with observational and system-log data, and integrate multiple regression or structural equation modelling to estimate the combined effect of both predictors and to test engagement as a mediator between the impact of learning analytics and achievement. Causal evidence could be strengthened by intervention studies that train teachers to act on analytics. Other factors that might be considered as a potential predictor, such as math anxiety, teacher efficacy, instructional materials, and parent involvement, should also be explored.

7. Conclusion and Recommendations

The results of this study showed that classroom engagement was significant in predicting senior secondary school students' mathematics achievement, while learning analytics as it is currently practiced was not. Students felt that their teachers monitored their progress, gave feedback and used assessment records, though this was not yet linked to achievement. The study concludes that, at present, the power of learning analytics is limited by the lack of infrastructure, teacher competence and systematic translation of data into instructional action, and that, the improvement of classroom engagement is a more effective lever for raising mathematics achievement. The following recommendations are based on these findings:

1. The mathematics teachers need to use learner centred approach such as cooperative learning, classroom discussion, inquiry-based and problem-based learning and peer tutoring to enhance the students' active learning in the classroom.
2. Teachers should foster students' interest in asking questions, offering ideas and working together to solve mathematical problems, and should pay special attention to enhancing students' participation in class.
3. School leaders need to create opportunities and professional development for teachers to employ learning analytics tools to detect learning gaps and provide timely and targeted interventions.
4. Ministries of Education should invest in digital learning infrastructure such as learning management systems and internet connectivity that facilitate effective implementation of learning analytics in secondary schools.
5. Regular workshops on engagement promoting and data-informed teaching strategies should be organised by school principals..

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Cite this article:

Author(s), POPOOLA Abiodun Agnes, AKINLUYI Oluwatoyin Abigeal, BUKOLA Oladele Oladayo, (2026).“ Predicting Mathematics Achievement through Learning Analytics and Classroom Engagement among Senior Secondary School Students in Nigeria”, ***Name of the Journal:*** Commonwealth Journal of Academic Research, (CJAR.EU)**, P,** 1 - 14. DOI: http://doi.org/10.5281/zenodo.24218259 **,** Issue: **10,** Vol.: **7,** Article: **1,** Month: **October,** Year: **2026.** Retrieved from https://www.cjar.eu/all-issues/

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