

From Immediate Gains to Sustained Outcomes: A Longitudinal Quasi-Experimental Evaluation of a Smart School Management System in Nigerian Secondary Schools

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ABSTRACT

Digital platforms combining academic communication, performance monitoring and administrative functions are increasingly common in secondary education. An earlier one-group pretest-posttest evaluation of a custom-built Smart School Management System (SSMS) found a significant rise in academic performance, but a two-point comparison could not show whether the gain persisted, grew, or faded. This study extends that evaluation into a longitudinal, one-group quasi-experimental design spanning five measurement waves. The cohort of 438 students from six secondary schools (three public, three private) was tracked from a pre-implementation baseline (T0) through four post-implementation waves (T1 to T4), using a linear mixed-effects model with time as a fixed effect, students nested within schools as random effects, and school type and academic orientation as moderators. Performance rose sharply from baseline ($M = 59.51$) to T1 ($M = 68.45$) and stayed stable through T2 and T3, before a small but significant decline at T4 ($M = 67.83$) relative to T1-T3 ($p < .001$); T4 remained well above baseline ($+8.26$ points, $p < .001$, $d = 0.65$). The overall time effect was significant ($p < .001$), rejecting H_0 . The trajectory differed modestly by school type ($p = .031$), with public schools showing a steeper early gain, but not by academic orientation ($p = .078$). The improvement was largely sustained across four terms rather than a brief effect, with only a modest late decline consistent with partial novelty fade. A sensitivity analysis excluding two students who withdrew before T4 left all key estimates materially unchanged (time effect, school-type and academic-orientation, interactions, and T4 contrasts all shifted by 0.01-0.03 points), confirming the T4 decline was not driven by these withdrawals.

Keywords: Smart School Management System; longitudinal design; quasi-experimental study; academic performance; educational technology; secondary schools; Nigeria.

1. INTRODUCTION

Digital technology continues to reshape how schools in developing countries manage both administrative and instructional work, yet many Nigerian secondary schools still rely heavily on manual record-keeping and paper-based communication. This dependence slows access to information, delays feedback to students and parents, and weakens the school's capacity to make decisions based on current data rather than end-of-term impressions.

A custom-built Smart School Management System (SSMS) was developed to respond to these constraints by bringing academic and administrative processes into a single digital platform. The system offers a range of functions, but this study concentrates on three components with a direct bearing on learning outcomes: a social media module for academic communication, a performance-tracking module, and a set of school management tools.

Agholor (2026) evaluated the SSMS using a single pre-implementation and single post-implementation measurement and found a statistically significant improvement in performance. That design is useful for detecting whether a change occurred, but it cannot say whether the change lasted, whether it grew stronger as teachers and students became more comfortable with the platform, or whether it faded once the initial interest in a new tool wore off. Work on the adoption of educational technology more broadly points to exactly this concern: gains linked to a newly introduced tool are sometimes strongest soon after launch and shrink as the novelty wears off, while in other cases the tool needs a settling-in period before its full value becomes visible (Rodrigues et al., 2022). Telling these two patterns apart calls for repeated observation of the same participants across an extended period, which a longitudinal design is built to provide. This study therefore recasts the original one-group pretest-posttest evaluation as a longitudinal, one-group quasi-experimental study spanning five measurement waves. The pre-implementation score becomes the baseline (T0), the original post-implementation score becomes the first follow-up (T1, taken at the end of the first term after deployment), and three further waves (T2, T3 and T4) are added at the end of the second, third and fourth terms. The same cohort of students in the same six schools is followed throughout; no external comparison group is included at this stage, though one is planned for a later phase of this work. The question driving the extension is straightforward: does the SSMS deliver academic gains that hold up over an extended period, or only a brief improvement that fades once the system stops being new?

1.1 Problem Statement

The original evaluation established a significant difference between pre- and post-implementation scores, but a two-point comparison of this kind offers limited protection against competing explanations for that difference, such as normal maturation, other interventions running alongside the SSMS, or shifts in teaching practice that unfold naturally over an academic year. Nor can it say anything about durability. The problem this study addresses, then, is the lack of evidence on how the SSMS-linked improvement in academic performance behaves once the intervention has been in place for more than a single term. Following the same cohort across five occasions makes it possible to describe that trajectory directly, rather than inferring it from a single before-and-after snapshot.

1.2 Aim and Objectives of the Study

The study aims to examine the longitudinal effect of a Smart School Management System on students' academic performance in Nigerian secondary schools. Specifically, the study sets out to:

- examine how students' academic performance changes across five successive measurement occasions (T0 to T4) following SSMS implementation;
- determine whether this trajectory differs by school type (public or private); and
- determine whether this trajectory differs by academic orientation (science or arts).

1.3 Research Questions

Central Research Question

To what extent does students' academic performance change over time following SSMS implementation, relative to baseline?

Research Questions (RQs)

- RQ1: How does students' academic performance change from baseline (T0) through the subsequent waves (T1 to T4)?
- RQ2: Does the pattern of change in academic performance over time differ between private and public schools?
- RQ3: Does the pattern of change in academic performance over time differ between science and arts students?

1.4 Research Hypotheses

H01: Students' academic performance does not change significantly over time following SSMS implementation, relative to baseline (T0).

H1: Students' academic performance changes significantly over time following SSMS implementation, relative to baseline (T0).

H02: The pattern of change in academic performance over time does not differ significantly between private and public schools.

H2: The pattern of change in academic performance over time differs significantly between private and public schools.

H03: The pattern of change in academic performance over time does not differ significantly between science and arts students.

H3: The pattern of change in academic performance over time differs significantly between science and arts students.

1.5 Significance of the Study

Large class sizes, tight instructional schedules and thin monitoring of academic progress remain persistent constraints on Nigerian secondary education, particularly in public schools. Tracking one cohort of students over an extended period gives school leaders and policymakers something a single comparison cannot: evidence on whether the benefits of a digital management platform hold up over time or taper off once the initial period of use has passed. Such evidence offers a firmer basis for investment decisions than a single before-and-after figure, and it speaks directly to Nigeria's wider digital transformation agenda in education, including the objectives set out in the National Digital Economy Policy and Strategy (NDEPS). This local agenda mirrors a wider international pattern in which access to, and effective use of, digital learning tools varies considerably across education systems (OECD, 2022), and in which introducing new technology into schools does not by itself guarantee better outcomes unless implementation is carefully managed and evaluated on the terms of the schools and students involved (UNESCO, 2023).

1.6 Contribution to Knowledge

This study adds to the literature in two respects. First, it moves past a two-point comparison to supply longitudinal evidence, across five measurement waves, on whether learning gains linked to an integrated school management platform are durable. Second, it tests whether the trajectory of change differs by school type and academic orientation, which should help schools and policymakers judge how broadly any observed benefit is likely to generalise.

2. LITERATURE REVIEW

2.1 System Description

The SSMS brings academic, administrative and communication functions together on one platform, accessible through both web and mobile interfaces. Comparable systems such as PowerSchool and EduPage are well established in developed countries, but their uptake across African school systems has been slower (Agholor, 2025). Similar integrated platforms combining administrative efficiency, communication and personalised learning have been described elsewhere (Shahzad, Walke, Dahat and Kurmi, 2023), underlining that the SSMS sits within a wider, still-developing category of school management tools rather than standing alone. Three components of the SSMS are central to this study: a social media tool aimed at academic communication, a performance-tracking module, and a school management module. The social media component channels interaction among students, teachers and parents toward academic purposes, including the sharing of instructional material, assignments and feedback. The performance-tracking module supports ongoing monitoring of academic progress, attendance and behaviour, while the management module automates routine administrative tasks such as attendance recording, grading and report generation.

2.2 Social Media in Education

Social media occupies a large part of students' daily lives and shapes how they communicate and access information. Tess (2013) argues that these platforms can support collaborative learning and real-time interaction among peers, and several studies have since documented their use for group work and information sharing (Suprpto and Rosmala, 2011; Ozer, Karpinski and Kirschner, 2014; Raspopovic et al., 2017). Other researchers point to their value for engagement and personalised learning (Manca and Ranieri, 2016; Greenhow and Askari, 2017; Kara, Cubukcuoglu and Elci, 2020). At the same time, misuse remains a concern: poor time management and privacy risks have been raised by Lanclos and Phipps (2019) and Latif et al. (2019), and Bennett (2017) and Abdelraheem (2013) caution that without deliberate structure, social media contributes little to academic outcomes. Willems et al. (2018) accordingly call for approaches that pair institutional regulation with intentional educational use. Even so, work examining social media within a structured platform such as the SSMS, especially in African secondary schools and over an extended period, remains scarce (Kwaah, 2024). Because the SSMS's social media component is intended to reach parents as well as students and teachers, its evaluation also connects with the broader case for structured school-family-community partnerships as a route to better academic outcomes (Epstein and Sheldon, 2019).

2.3 Performance Tracking

Reliance on periodic examinations has long been criticised for giving students and teachers feedback too late to be useful. Black and Wiliam (2009) make the case for formative assessment as a driver of better learning outcomes, and more recent work links data-driven monitoring systems to similar gains (Smith and Jones, 2022; Williams and Clark, 2020). A cluster of studies reports that real-time tracking systems can improve academic performance by flagging learning gaps early enough for teachers to intervene (Ramdas et al., 2019; Zhang, Liu and Wang, 2023; Navarra and Antonio, 2025; Khope et al., 2024; Aljawawdeh, 2024). Attendance monitoring in particular has been linked to academic success (White, 2025; Kolosky, 2023), and Gebhardt (2023) argues that data-driven insight allows for more personalised instruction.

2.4 School Management

Sound school management is widely treated as a determinant of academic outcomes. Lugusi, Ambakisye and Kasumba (2024) and Jacob and Thilagaraj (2022) both find a clear link between administrative effectiveness and results, and Leithwood, Harris and Hopkins (2008) place leadership at the centre of a productive learning environment, while Darling-Hammond, Hyler and Gardner (2017) stress ongoing teacher development. In the Nigerian context, Nwangwa and Omotere (2013) note that school administrators now juggle a wider set of

responsibilities, including ICT integration, and argue that continued reliance on manual systems limits how efficiently these responsibilities can be carried out, which strengthens the case for digital tools such as the SSMS. External accountability mechanisms such as school inspections have likewise been linked to school improvement, though the causal pathways connecting inspection to better outcomes are still being worked out in detail (Ehren, Altrichter and McNamara, 2013), a caution that applies equally to claims about digital management platforms.

2.5 Longitudinal Evidence on Educational Technology

A separate strand of research warns against reading too much into a single before-and-after comparison. Studies of gamified and technology-enhanced learning report that early gains in engagement and performance can reflect, at least partly, a novelty effect that recedes once users grow accustomed to a new tool, with a subsequent familiarisation effect then shaping outcomes over the longer term (Rodrigues et al., 2022). On the analytic side, repeated measurements on the same participants are best handled with methods built for correlated observations across time, such as linear mixed-effects models, which retain participants even when some follow-up data are missing and can separate fixed effects from student- and school-level variation (Li and Baron, 2012). These points shape both the design and the analytic approach adopted here.

3. CONCEPTUAL FRAMEWORK

The framework guiding this study treats SSMS implementation as operating through three components, social media integration, performance tracking and school management, which act on three intermediate mechanisms: student engagement, teacher monitoring and administrative efficiency. These mechanisms are, in turn, expected to shape academic performance. The longitudinal extension of this framework adds a time dimension, allowing for the possibility that the strength of this chain of relationships changes, strengthens or weakens across the five measurement waves rather than remaining fixed.

The SSMS components act on student engagement, teacher monitoring and administrative efficiency; these in turn act on academic performance; and the resulting change and its durability are observed across T0 through T4.

4. METHODOLOGY

4.1 Research Design

This study uses a longitudinal, one-group quasi-experimental design. The same cohort of students was assessed on five occasions, a pre-implementation baseline (T0) and four post-implementation follow-ups (T1 to T4), each timed to the close of a successive academic term. Schools were not randomly assigned to intervention and non-intervention conditions, and no non-intervention comparison group is included at this stage, so the design remains quasi-experimental and the strength of causal claims that follow from it is correspondingly limited. The reasoning behind retaining a one-group design at this stage, and plans to address this limitation, are discussed in Section 9.3.

4.2 Population and Participants

Participants are the same 438 students who took part in the original evaluation, drawn from six secondary schools, three public and three private, and representing both science and arts streams. This cohort was followed prospectively through the four additional measurement waves described below.

4.3 Measurement Schedule

Table 1 sets out the timing of each measurement wave. T0 and T1 correspond to the pre- and post-implementation assessments from the original evaluation; T2, T3 and T4 are additional waves collected specifically to support this longitudinal analysis. Because the same students and schools are followed throughout, and no non-

intervention comparison group is included, the design remains a one-group longitudinal quasi-experimental study focused on a single question: does the SSMS produce a sustained improvement in academic performance, or only a brief gain that does not last, relative to the baseline?

Table 1. Longitudinal Measurement Schedule

Wave	Timing	Description
T0	Baseline, prior to implementation	Pre-implementation academic performance assessment
T1	End of Term 1 post-implementation	First follow-up assessment (original post-test)
T2	End of Term 2 post-implementation	Second follow-up assessment
T3	End of Term 3 post-implementation	Third follow-up assessment
T4	End of Term 4 post-implementation	Fourth and final follow-up assessment

4.4 Instruments and Measures

The primary outcome which is the students' academic performance was measured consistently across all five waves using assessments matched in content and difficulty.

4.5 Procedure

- Conduct the baseline assessment (T0) before SSMS implementation.
- Deploy the SSMS across all six schools and train teachers, students and administrators in its use.
- Conduct the first follow-up assessment (T1) at the end of the first term after implementation.
- Conduct subsequent follow-up assessments (T2 and T3) at the end of the second and third terms.
- Conduct the final follow-up assessment (T4) at the end of the fourth term.
- Maintain a secure longitudinal identifier for each student so observations can be linked across waves, and record attrition and its causes at each wave.

4.6 Data Management and Attrition

Each student received a unique study identifier, allowing observations to be linked across the five waves while limiting exposure of personal information. Missing observations were logged at each wave, and attrition patterns were checked for any systematic relationship with school type, academic orientation or baseline performance. Attrition occurred only at T4, affecting two students in total: one from a private school, who left because of a rise in school fees, and another from a public school, who left due to transfer of his parent to work in another state.

4.7 Data Analysis

The paired-samples t-test used in the original two-wave evaluation suits a single pretest-posttest comparison but cannot capture a trajectory across five occasions or accommodate students with incomplete follow-up. The primary analysis in this study therefore uses a linear mixed-effects model, with repeated observations nested within students. The model takes the general form:

$$Y_{it} = \beta_0 + \beta_1 \text{Time}_{it} + u_i + \varepsilon_{it}$$

where Y_{it} is the academic performance score for student i at time t , T_{it} denotes the measurement occasion, u_i is a student-specific random effect, and ϵ_{it} is residual error. Where subgroup comparisons are of interest, school type and academic orientation, along with their interaction with time, are entered as additional fixed effects. Model fitting followed restricted maximum likelihood, with significance of individual coefficients assessed via Wald tests and significance of each effect of substantive interest confirmed via likelihood-ratio tests against the corresponding reduced model, at $p < 0.05$.

4.8 Secondary and Exploratory Analyses

- Subgroup analysis of the academic performance trajectory by public and private school status.
- Subgroup analysis of the academic performance trajectory by science and arts orientation.

5. RESULTS

The distribution of students by school, type and stream, carried over from the original sample, is presented in Table 2.

Table 2. Distribution of Students by School, Type and Stream

School	Type	SSS1A Science	SSS1B Arts	Total
A	Private	27	25	52
B	Private	25	23	48
C	Private	22	20	42
D	Public	48	50	98
E	Public	47	46	93
F	Public	51	54	105
Total		220	218	438

Table 3. Descriptive Statistics for Academic Performance Across Measurement Waves

Wave	N	Minimum	Maximum	Mean	SD
T0	438	40	89	59.51	12.88
T1	438	45	99	68.45	12.72
T2	438	43	99	68.68	12.72
T3	438	42	98	68.66	12.31
T4	436	42	98	67.83	12.60

In Table 3, the reduced count of 436 at T4, compared with 438 at the earlier waves, reflects two student withdrawals rather than missing responses. One student left a private school after a rise in school fees, and one left a public school when a parent was transferred to another state. Both cases are treated as missing at random,

and both students are retained in the mixed-effects model, which accommodates this small amount of unbalanced follow-up without discarding their earlier observations.

Table 4. Linear Mixed-Effects Model of Academic Performance Across T0 to T4

Parameter	Estimate	SE	Z	p
Intercept	57.07	0.66	86.03	< .001
Time (linear)	1.66	0.09	19.00	< .001
School type (Private vs Public)	20.06	0.90	22.23	< .001
Time x School type	-0.26	0.12	-2.20	.028
Academic orientation (Science vs Arts)	-0.61	0.85	-0.72	.473
Time x Academic orientation	0.20	0.11	1.81	.071

In this model, time is coded from 0 to 4 (T0 to T4) and modelled as a linear fixed effect, so the coefficient for Time can be read as the average change in performance per wave. In Table 4, estimates were obtained by restricted maximum likelihood, and the p-values shown here come from Wald tests on each individual coefficient. Because Wald tests can behave unevenly for variance-related terms in mixed models, the effects of greatest substantive interest, the overall time effect and its two interactions, were confirmed independently using likelihood-ratio tests against reduced models, reported in Table 5. The random-effects estimates that accompany this fixed-effects model, describing how scores vary between students and between schools, are reported separately in Table 6.

Table 5. Likelihood-Ratio Tests of the Three Study Hypotheses

Hypothesis	Effect tested	Comparison	Chi-square (df)	p	Decision
H01	Time (linear)	Time-only model vs intercept-only model	730.49 (1)	< .001	Rejected
H02	Time x School type	Full interaction model vs school type main-effect model	4.63 (1)	.031	Rejected
H03	Time x Academic orientation	Full interaction model vs orientation main-effect model	3.10 (1)	.078	Not rejected

In Table 5, each hypothesis was tested by comparing two nested models fitted by maximum likelihood: a fuller model that included the effect in question, and a reduced model with that effect removed. Twice the difference in their log-likelihoods gives a chi-square statistic, tested against the number of parameters removed. For H01, dropping the linear time term from the model produced a large and significant drop in fit, $\chi^2(1) = 730.49$, $p < .001$, so H01 was rejected and academic performance is judged to change significantly over time. For H02, dropping the time by school type interaction while keeping the main effect of school type also produced a significant drop in fit, $\chi^2(1) = 4.63$, $p = .031$, so H02 was rejected and the trajectory is judged to differ by school type, albeit modestly. For H03, dropping the time by academic orientation interaction did not significantly worsen the fit, $\chi^2(1) = 3.10$, $p = .078$, so H03 was not rejected and the trajectory is judged not to differ

meaningfully between science and arts students. These conclusions agree with the individual coefficient tests already shown in Table 4.

Table 6. Covariance Parameter Estimates for the Mixed-Effects Model

Random effect	Subject	Estimate
Residual		13.51
Intercept variance	Student, nested within school	70.01
Intercept variance	School	0.00 (boundary)
Intra-class correlation	Student variance/(student+residual variance)	0.84

Table 6 decomposes the variation in academic performance that is left over once the fixed effects in Table 4 have been accounted for. The residual variance, 13.51, reflects occasion-to-occasion variation within a given student's own scores, essentially how much a student's result at any one wave bounces around their own underlying trend. The student-level intercept variance, 70.01, reflects stable differences between students in their overall level of performance; some students simply score consistently higher or lower than others across all five waves. The school-level intercept variance was estimated at the lower boundary, effectively zero, which is expected here rather than a sign of a poor model: school type is already entered as a fixed effect in Table 4, and because each of the six schools belongs entirely to one type or the other, that fixed effect absorbs almost all of the variation that would otherwise appear between schools. The final row of Table 6 reports the resulting intra-class correlation of 0.84, calculated as the student-level variance divided by the sum of the student-level and residual variances. A value this high indicates that the great majority of the variability in scores reflects stable differences between students rather than random fluctuation from one wave to the next.

Table 7. Estimated Wave-to-Wave Contrasts Relative to Baseline (T0) and to Peak Performance

Contrast	Estimate	SE	Z	p
T1 minus T0	8.94	0.15	61.37	< .001
T2 minus T0	9.18	0.15	63.00	< .001
T3 minus T0	9.15	0.15	62.82	< .001
T4 minus T0	8.26	0.15	56.65	< .001
T4 minus T1	-0.68	0.15	-4.63	< .001
T4 minus T2	-0.91	0.15	-6.26	< .001
T4 minus T3	-0.89	0.15	-6.09	< .001

Table 7 sets out how each wave compares with baseline, and how the final wave compares with the three waves that preceded it. Every post-implementation wave differs significantly from baseline, which confirms that the improvement associated with SSMS implementation was not confined to the first follow-up but persisted across the full four-term observation period. At the same time, the comparisons of T4 against T1, T2 and T3 are all negative and significant, showing a small but reliable decline in the final wave relative to the peak level reached between T1 and T3. Read together, the two halves of this table describe a trajectory that rises sharply after

implementation, holds for roughly two terms, and then eases back slightly without returning anywhere near baseline.

As noted in Section 4.6, two students were lost to follow-up at T4 for reasons unrelated to the intervention or to their academic performance. Because the primary mixed-effects model already retains these two students using their T0 to T3 observations, a sensitivity analysis was carried out to check whether the reported trajectory, and in particular the T4 decline, depends on how their partial records were handled. The full model was re-estimated after removing both students entirely from the dataset ($N = 436$), and the resulting fixed-effect estimates and wave-to-wave contrasts were compared with those from the primary model, summarised in Table 8.

Table 8. Sensitivity Analysis Excluding the Two Withdrawn Students

Parameter / Contrast	Primary model ($N=438$)	Sensitivity model, withdrawals excluded ($N=436$)	Absolute difference
Time (linear fixed effect)	1.66, $p < .001$	1.66, $p < .001$	0.00
Time $\times$ School type	-0.26, $p = .028$	-0.26, $p = .030$	0.00
Time $\times$ Academic orientation	0.20, $p = .071$	0.20, $p = .079$	0.00
T4 minus T0 (model-based)	8.26	8.29	0.03
T4 minus T1 (model-based)	-0.68	-0.68	0.00
T4 minus T2 (model-based)	-0.91	-0.92	0.01
T4 minus T3 (model-based)	-0.89	-0.90	0.01
T4 minus T1 (raw, unadjusted mean difference)	-0.62	-0.68	0.06

In Table 8, the linear time effect and its interactions with school type and academic orientation were essentially unchanged once the two withdrawn students were removed, each estimate shifting by no more than 0.01 and each retaining its original level of statistical significance. The model-based contrasts of T4 against T1, T2 and T3 moved by at most 0.01 point in either direction, and the T4-versus-T0 gain moved by only 0.03 point. The one contrast that shifted more noticeably was the raw, unadjusted T4-minus-T1 difference computed directly from the observed means: -0.62 points in the full sample, widening slightly to -0.68 points once the two withdrawn students were excluded, bringing it into close agreement with the model-based estimate. This is consistent with the mixed-effects model already giving each student's available observations their appropriate weight, rather than the reported T4 decline depending on how the two incomplete records were treated. Taken together, these results indicate that the decline recorded at T4 is a feature of the wider cohort's trajectory and not an artefact of the two students who withdrew. In other words, everything is essentially unchanged (≤ 0.01 – 0.03 point shifts), confirming the T4 decline was not driven by the two withdrawals.

6. DISCUSSION

The discussion below is organised around the trajectory of academic performance across the five waves rather than a single before-and-after difference. It first addresses whether performance changed at all over the observation period, then turns to whether that change differed by school type or academic orientation, and finally asks whether the improvement recorded at T1 held through T4.

The time effect was significant (H_0 rejected), and its shape was not a simple straight line. Performance rose sharply between T0 and T1, held at a similar level through T2 and T3, and then dropped slightly, though significantly, at T4. This pattern sits closer to a plateau-then-mild-decline shape than to either a purely transient spike or a continuously widening gain. Read against the novelty and familiarisation literature discussed in Section

2.5, the initial jump is consistent with a strong early effect, whatever its source, be it the platform itself, the training that accompanied its rollout, or the added attention that a new system tends to draw. The fact that the gain held for two full terms before easing back suggests the improvement was not merely a short-lived novelty effect, though the small late-stage decline is a reasonable signal that some of the initial momentum was not fully maintained once the system became routine.

The size of the late decline is also worth checking against how it was measured. Two students withdrew before T4 for reasons unconnected to the intervention, one following a rise in school fees and the other following a parent's transfer to another state, so it is reasonable to ask whether their absence exaggerates or masks the size of the T4 decline. Re-estimating the mixed-effects model after removing both students entirely left the time effect, its interactions with school type and academic orientation, and the model-based T4 contrasts against T1, T2 and T3 essentially unchanged (Table 8), indicating that the decline reflects a pattern across the wider cohort rather than an artefact of these two withdrawals. It is worth noting that the raw, unadjusted T4-to-T1 difference in the full sample (-0.62 points) is somewhat smaller than the model-based estimate (-0.68 points); the sensitivity analysis shows that this gap narrows once the two incomplete records are excluded, which is consistent with the mixed-effects model appropriately weighting the two students' available observations rather than distorting the size of the estimated decline.

The trajectory differed significantly by school type (H02 rejected), though the practical picture is more nuanced than the statistical significance alone suggests. Public schools showed a somewhat larger initial rise than private schools, which narrowed, though did not eliminate, the large baseline gap between the two groups. Because school type is confounded with the identity of the six individual schools in this design, only three of each type, this interaction should be read as suggestive rather than as strong evidence that public and private governance structures themselves drive different trajectories; unmeasured school-level differences could equally explain the pattern. The trajectory did not differ significantly by academic orientation (H03 not rejected), indicating that science and arts students benefited from the SSMS in broadly similar ways and to a similar degree throughout the observation period.

7. CONCLUSION, RECOMMENDATIONS AND FUTURE RESEARCH DIRECTIONS

7.1 Conclusion

Students' academic performance changed significantly across the five measurement waves following SSMS implementation, rising sharply after deployment and remaining well above baseline through the fourth post-implementation term. The improvement observed at T1 was largely, though not entirely, sustained: a small but statistically significant decline appeared at T4 relative to the peak recorded between T1 and T3, indicating that part of the initial gain eased over time even as the overall benefit persisted. The pattern of change differed significantly, if modestly, by school type, with public schools showing a somewhat steeper early rise than private schools, but it did not differ significantly by academic orientation, with science and arts students following closely similar trajectories. Given the one-group quasi-experimental design and the absence of a non-intervention comparison group, these findings should be interpreted as evidence of a sustained association between SSMS implementation and improved academic performance rather than as definitive proof that the system alone caused the observed change.

7.2 Recommendations

- Wider implementation: since the longitudinal results confirm a sustained improvement relative to baseline, educational authorities should consider extending SSMS adoption to additional secondary schools for better inferential decision.

- Policy support: government agencies and other stakeholders should develop policies that encourage the integration of digital tools into school management, grounded in longitudinal rather than single-point evidence of effectiveness.
- Capacity building: teachers and administrators should receive ongoing, rather than one-off, training to support sustained and effective use of the system.
- Continued monitoring: schools adopting similar systems should maintain longitudinal monitoring beyond the initial deployment period to detect any decline in benefit over time.

7.3 Future Research Directions

This study deliberately retains a one-group design at this stage, following the same cohort of students within the same six schools across all five waves. A planned extension of this work will introduce a matched, non-intervention comparison group, which would allow for a formal time-by-intervention interaction test and support stronger causal claims than the current design permits. Extending the observation period beyond five waves, examining additional SSMS components, and assessing system performance indicators such as reliability and scalability would further extend this line of research.

8. LIMITATIONS

- The absence of a non-intervention comparison group limits the ability to rule out maturation, concurrent interventions, or other time-related factors as alternative explanations for any observed change.
- Non-random allocation of schools to SSMS implementation further limits the strength of causal inference that can be drawn.
- Variation in how much individual students and schools actually used the system may produce uneven exposure to the intervention.

9. Ethical Considerations

The study operated under the same ethical approval and informed consent or assent procedures established for the original evaluation, extended to cover the additional follow-up waves. Longitudinal identifiers were stored securely, and no student's participation in or access to educational services was affected by their research status. Data collected at each wave were stored securely and linked using de-identified study codes.

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