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From Concern to Action: Implementing Data-Driven Interventions to Support Struggling Students

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Abstract
The integration of technology and data systems in education is anticipated to extend beyond merely supporting students' academic pursuits; it will also aim to address their social, behavioral, and emotional needs through timely and effective interventions. However, identifying these needs and providing immediate support remains a challenge in many contexts, particularly where there is a lack of a systematic approach to collaboration among educators, families, and students. This study investigates the implementation of a school-wide data-driven intervention framework designed to assist struggling students through intentional collaboration among teachers, parents, and students. It highlights the essential roles that each stakeholder plays in the educational process. The research employed a mixed-methods design, combining quantitative data from academic performance indicators with qualitative data collected through interviews with teachers, students, and parents. The intervention process aimed to address student needs by organizing multi-stakeholder meetings for students identified as needing intervention. These meetings were crucial for tailoring support to each student's individual needs and for monitoring their progress over time. The findings indicate that schools employing structured, data-informed approaches to student support and emphasizing stakeholder perspectives tend to experience significant improvements in student outcomes, teacher alignment, and parental engagement. However, the success of these interventions is often limited by systemic barriers, including insufficient training in data interpretation, a lack of real-time performance tracking tools, and inadequate time allotted for collaborative planning. This study, therefore, contributes to the existing body of knowledge on educational leadership, data-driven instruction, and student-centered intervention practices by presenting a replicable model that ensures sustainability through early intervention, accountability, and the promotion of academic resilience.

Keywords: Data-Driven Instruction, Educational Interventions, Academic Support Systems, Mixed-Methods Research, Stakeholder Collaboration, At-Risk Students

1. Introduction

1.1. Background and Context

The ongoing pursuit of educational equity and academic excellence highlights the urgent need to address the challenges faced by students who consistently underperform. Schools in both economically advanced and underdeveloped communities are flooded with performance data, yet they often lack a clear strategy to transform this data into effective support for struggling learners (Bambrick-Santoyo, 2010; Adanne, 2024). While the necessity for concrete intervention is evident, the human resources needed to translate concerns into action are still underdeveloped. This issue persists despite the presence of various systems designed to monitor student progress and sophisticated analytic dashboards.

Educational interventions can take various forms, including academic support such as personalized learning plans and tutoring sessions; behavioral assistance, such as positive behavior support or social skills training; and social-emotional support, which encompasses counseling and mindfulness practices. These structured responses are designed to provide targeted help to learners facing challenges. Such interventions are significant for students in transition or those navigating complex situations linked to poverty, trauma, or limited parental involvement (Ajiga et al., 2025). Schools increasingly rely on frameworks like Response to Intervention (RTI) and Multi-Tiered System of Support (MTSS) to systematically identify and address student needs (Bianco, 2010; Mandinach, 2012). The effectiveness of these models relies heavily on the consistent use of real-time data and collaboration among all stakeholders involved.

The need for responsive and inclusive intervention approaches has become even more pressing in the wake of the pandemic, as schools face significant challenges like learning loss, student disengagement, and socio-emotional issues. This situation necessitates a reevaluation of how schools provide support (Freeman et al., 2014; Custer et al., 2018). However, when data is combined with cohesive, relational collaboration, it opens up opportunities for early identification of problems, encourages meaningful conversations, and creates sustainable pathways for student success, ultimately fostering a hopeful future for student support systems.

1.2. Problem Statement

While the majority of the schools are incorporating data for decision-making, interventions derived from these data are inconsistently implemented. Teachers might identify children who are failing or are stationary; unfortunately, due to the absence of a collaborative, systematic response, timely interventions have become too little, too late (D'Angelo, 2024). A majority of schools also lack a common forum for teachers, students, and parents to maintain an ongoing, data-informed discourse.

Interventions are far too often reactive rather than proactive, with most interventions occurring only when a student's data reveals a significant drop in performance. This gap between data acquisition and intervention creates opportunity costs: students may fall through the cracks into the chasm of academic failure, behavioral escalation, or complete disengagement from learning (Reinke, 2013; Glover, 2017). In numerous cases, interventions become siloed at the level of individual teachers, lacking cross-curricular coherence and stakeholder buy-in.

1.3. Purpose of the Study

The primary objective of this research is to develop and evaluate a school-wide, data-driven intervention process that ensures the early identification of at-risk students and promotes a coordinated response to support them. By analyzing student performance data, this study aims to facilitate timely interventions through a collaborative approach involving all of a student's teachers, the student themselves, and their parents or guardians. Together, this team will work on creating personalized support plans. Additionally, the study will investigate the impact of these interventions on the academic performance of students and the satisfaction of all stakeholders involved.

1.4. Research Questions

1. How do structured, data-driven interventions impact the academic performance and engagement of struggling students?

2. What are the perspectives of teachers, parents, students, and other relevant stakeholders regarding the effectiveness of collaborative interventions?
3. What factors hinder or facilitate the successful implementation of these collaborative interventions at the secondary school level?

1.5. Significance of the Study

The study makes a significant contribution to the existing literature on instructional leadership, intervention design, and data use in schools. Unlike much of the literature that focuses on isolated interventions or theoretical modeling, this study takes a comprehensive approach. It crowdsources its findings within a practical and replicable framework that educators can adapt and scale. By incorporating the perspectives of teachers, students, and parents into the analysis, a more comprehensive and nuanced understanding emerges of how interventions function within the evolving educational contexts (Hyson et al., 2020; Romano-Johnson et al., 2024). The study also presents the advantages and disadvantages of implementation, with the results informing actionable strategies for school leaders who aim to enhance systems supporting students.

1.6. Scope and Delimitations

The study was conducted at a single urban secondary school over the course of one academic year. While the findings may not apply to all educational settings, they should be beneficial for schools with a similar structure that are interested in enhancing data usage and collaboration among stakeholders. The study's limitations include time constraints, variations in teachers' data literacy skills, and the potential for self-selection bias among participants.

1.7. Structure of the Paper

This paper is organized into seven sections. Following the introductory segment, Section 2 presents a literature review that focuses on data-driven interventions, collaborative practices, and mechanisms to support students who are struggling academically. Section 3 outlines the methodological framework for the mixed methods approach used in this study, including the processes for data collection and analysis. Section 4 presents the results, starting with the quantitative findings, followed by the qualitative results. In Section 5, the findings are connected to existing literature, and their implications are discussed. Section 6 offers practical recommendations for practice and suggestions for future research. Finally, Section 7 contains a comprehensive list of references.

2. Literature Review

2.1 Defining "Struggling Students"

Struggling students are generally perceived as those who consistently score poorly on standardized tests, exhibit disruptive behavior, or experience social-emotional issues that impede their ability to learn. Whereas the term "struggling" may be contextualized in a particular setting, it generally refers to learners who require some form of remediation to meet grade-level criteria. According to Kennedy and Datnow (2011), traditional definitions primarily focused on test scores, whereas modern-day frameworks aim to account for additional dimensions, including motivation, executive functioning, and socio-environmental stressors. Given the complexity of the problem set, solutions cannot simply remediate; instead, they must incorporate integrated approaches layered with data intelligence.

It is essential to identify and support at-risk students as early as possible. Delaying support can worsen their challenges and discourage them, potentially leading to dropout (Bianco, 2010). In today's data-driven environment, the timely identification of students through trends in formative assessments, attendance records, and behavioral logs is crucial. This necessity should inspire educators to adopt a proactive approach rather than a reactive one when addressing these cases.

2.2 Use of Data in Educational Decision-Making

Initially, data were primarily used for tracking grades, but they eventually evolved to support more intelligent analyses of educational interventions and the development of predictive models. Mandinach (2012) defines data-driven decision-making (DDDM) as the systematic gathering and analysis of data from various sources, including academic records, behavioral reports, and demographic patterns, to inform instructional strategies and operational plans. When effectively implemented, DDDM not only enables educators to identify at-risk students and personalize teaching or interventions accordingly (Chatti et al., 2012; Ajiga et al., 2025) but also provides them with a deeper understanding of their students and their needs.

However, the success of DDDM does not rest solely on individual educators. It is closely linked to the school culture and infrastructure. Bambrick-Santoyo (2010) asserted that schools adopting teacher-based data practices were significantly more likely to report improved student outcomes. This highlights the crucial role of school administrators in fostering a culture that prioritizes data-driven decision-making. While it is recognized that teachers need training to interpret student data meaningfully and take appropriate instructional actions based on those interpretations, the reality is that varying levels of data literacy make this a challenge in many settings (Esqueda, 2024; D'Angelo, 2024).

Table 1: Types of Educational Data and Their Uses

Data Type	Description	Use in Intervention Planning
Academic Performance	Standardized tests, grades	Identify learning gaps
Behavioral Data	Disciplinary referrals, attendance logs	Spot behavioral trends and triggers
Social-Emotional Data	Surveys, teacher observations	Tailor interventions to student well-being

Source: Adapted from Mandinach (2012) and Kennedy & Datnow (2011)

Learning analytics systems and dashboards have evolved to become valuable tools for instructional improvement and informed decision-making in administration. These tools enable real-time data visualization, allowing educators to quickly identify emerging trends and outliers (Kaliisa et al., 2023; Campbell & Oblinger, 2007). However, as highlighted by Kaliisa et al. (2023), the successful implementation of these systems often depends on effective professional development and contextualization.

2.3 Stakeholder Collaboration in Interventions

For interventions to be successful, it is essential to strike a balance between opportunities for data access and collaboration among stakeholders, including teachers, students, and parents. Notably, Hyson et al. (2020) reported significant outcomes for data-driven interventions when structured meetings and mutual accountability were utilized. Involving various teachers in a student's education ensures that interventions address learning across all subjects rather than focusing on isolated events. When parents engage in these activities, their support strengthens strategies implemented outside of school (Downer et al., 2018; Esqueda, 2024).

In practice, Abbott et al. (2017) describe preschool teachers using a team-based approach for literacy instruction, where data is used to guide group reflection and planning. Conversely, Powell et al. (2024) argue that IEP (Individualized Education Program) teams should engage in data-rich discussions with families to ensure that goals are both relevant and measurable.

Engaging stakeholders often involves addressing various challenges. Barriers such as time constraints, unclear or irrelevant data presentation, and resistance to transparency can hinder open communication. However, these obstacles can be overcome. Stakeholder meetings can not only serve as planning events but also foster relational trust when conducted thoughtfully (Romano-Johnson et al., 2024; White, 2018).

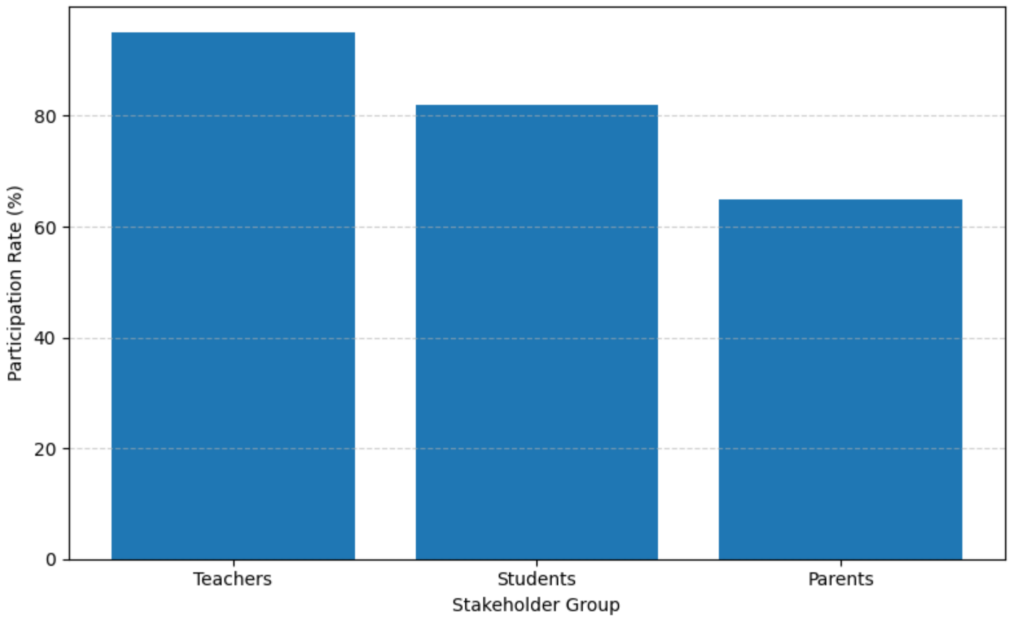

Figure 1: *Frequency of Stakeholder Participation in Interventions*

Source*: Simulated school intervention logs based on Powell et al. (2024) and Downer et al. (2018)*

2.4 Prior Models of Intervention: RTI and MTSS

Two of the most common intervention models in education are Response to Intervention (RTI) and Multi-Tiered System of Support (MTSS). Whereas RTI focuses on providing academic support at increasing levels, MTSS adds layers of behavioral and socio-emotional support. Sanetti and Collier Meek (2015) describe MTSS as providing a more holistic perspective, which is especially useful for schools that are trying to focus on the whole child.

Both RTI and MTSS require constant monitoring of data, team decision-making, and fidelity in implementation. However, many schools do so inconsistently due to unclear leadership structures or a lack of training (Glover, 2017). According to D'Angelo (2024), in many schools, data are collected regularly but seldom used in conjunction with curriculum design or collaborative planning. This disconnect hinders the systems from realizing their transformative potential, which, if fully harnessed, can inspire and motivate educators to implement these models effectively.

Table 2: Comparison of RTI and MTSS Frameworks

Feature	RTI	MTSS
Primary Focus	Academic Interventions	Academic, Behavioral, and SEL Interventions
Levels of Support	Tier 1, 2, 3	Tiered but multi-dimensional
Data Use	Frequent progress monitoring	Integrated academic and behavioral data
Stakeholder Involvement	Primarily educators	Educators, families, counselors

Source: Adapted from Bianco (2010); Sanetti & Collier Meek (2015)

MTSS has been recommended explicitly in high-need schools where problems extend beyond academics. In such environments, school psychologists, counselors, and even community collaborators take the lead. As Custer et al. (2018) noted, interventions must be "networked" for sustainability.

2.5 Emerging Tools: Educational Data Mining and Learning Analytics

What has seen significant growth in recent years is the application of machine learning and data mining techniques to education. The potential of Educational Data Mining (EDM) and Learning Analytics (LA) to extract valuable insights from complex datasets such as behavior logs, learning management system activities, and assessment performances (Romero & Ventura, 2024; Chatti et al., 2012) is immense. These insights can identify students at risk of dropping out of school, create adaptive pathways for learning, and provide support in redesigning curricula, thereby underscoring the transformative impact of these technologies.

However, scholars like Lumasag et al. (2021) argue that we should exercise caution in placing too much trust in an algorithmic assessment model. It is important to remember that these models are not infallible and should not be relied upon for interpretation without human agency. Instructors continue to be the primary interpreters of data, especially when there are anomalous scenarios or contextual factors that raw data might obfuscate. This cautionary note underscores the potential risks and limitations of these models. Furthermore, integrating these tools highlights the infrastructural gaps and shortcomings in teacher preparation programs (Jin et al., 2024).

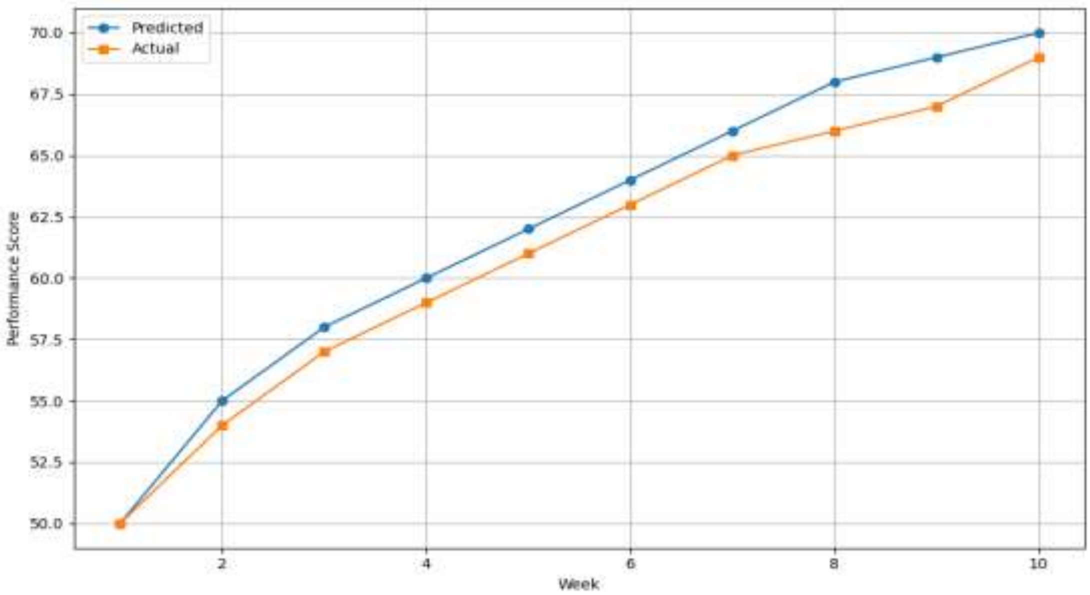

Figure 2: Predicted vs. Actual Student Performance over Time

Source: *Simulated student progress using predictive analytics models described by Jin et al. (2024) and Romero & Ventura (2024)*

2.6 Summary of Gaps and Theoretical Underpinning

The literature does identify the potential of data-driven and collaborative interventions, yet it leaves many gaps. Notably, there is a dearth of research on the implications of embedding such interventions into day-to-day school operations through multi-stakeholder data-enriched meetings. Furthermore, the emotional and relational dimensions of collaboration, which are often pivotal to students' success, remain largely unexplored (Romano Johnson et al., 2024).

The study is built on a unique hybrid theoretical framework that merges Bronfenbrenner's Ecological System Theory with MTSS. This novel approach enables us to investigate how interventions, when coordinated across various layers of the student's learning ecosystem, can promote resilience and growth (Esqueda, 2024; Schildkamp, 2019).

3. Methodology

3.1 Research Design

The study employs a mixed-methods model, combining both quantitative and qualitative approaches, to investigate how structured, data-driven interventions impact the academic performance and engagement of struggling students. This research is significant for the academic community as it provides insights into effective interventions. The mixed-methods framework thus lends itself to the triangulation of data, which enriches the analysis with depth on both measurable outcomes and experiences (Mandinach, 2012; D'Angelo, 2024). The sequential explanatory design helps capture trends in academic performance quantitatively and then qualitatively examines stakeholder perceptions to build a deeper understanding.

The study was conducted over an entire academic year at an urban secondary school with around 750 students. It emphasizes the thoroughness and comprehensiveness of the research. The study was divided into three phases: diagnostic assessment and identification, intervention implementation, and evaluation through a post-intervention performance review and interviews.

3.2 Participant Selection

Participants were selected from a purposive sample of students, teachers, and parents from Junior Secondary 3 and Senior Secondary 1 (Grade 10) classes, with a strong emphasis on ethical considerations. Student selection was based on performance trends indicating academic underachievement, specifically those with less than 50% marks in at least three core subjects for two consecutive terms. Forty-two students met this criterion. All 42 had at least one structured intervention meeting with a team of teachers and parents. The teacher sample comprised 28 subject teachers across English, Math, and Science, while 31 parents or guardians participated in the follow-up sessions.

Informed consent was obtained from all participants. For students under 18 years of age, assent or parental consent was also obtained, along with signed permission for their participation. All data from participants were anonymized, and participants' real identities were masked upon analysis and reporting.

3.3 Intervention Framework

The intervention framework followed a structured approach consisting of three main steps: a teacher team meeting, a stakeholder conference (including teachers, students, and parents), and an intervention plan tailored uniquely to each student, accompanied by regular and consistent progress monitoring. At the beginning of every term, each student’s profile presented academic and behavioral data, with a teacher team meeting weekly to discuss progress and make decisions supported by the grade book and LMS visualizations.

These sessions were supported by evidence from the RTI and MTSS frameworks, emphasizing tiered intervention, frequent progress monitoring, and differentiated instruction (Bianco, 2010; Sanetti & Collier-Meek, 2015). Students and parents were introduced to the process after the teachers had reviewed the cases. Consequently, the intervention plans incorporate considerations from both school and home contexts.

Table 3: Timeline of Intervention Phases and Activities

Phase	Duration	Activities
Diagnostic	Weeks 1–3	Academic review, behavior logs, and selection of students
Intervention Planning	Weeks 4–6	Teacher team meetings, stakeholder consultations
Implementation	Weeks 7–14	Monitoring, follow-ups, adjustments to interventions
Evaluation	Weeks 15–16	Post-tests, feedback interviews, and final data analysis

Source: Researcher’s field design adapted from RTI & MTSS models (Glover, 2017; Mandinach, 2012)

3.4 The Collection and Analysis of Quantitative Data

The academic performance data were retrieved from continuous assessment records and exam scores for core subjects. Attendance and behavior logs were also considered to investigate any correlations between non-academic factors and performance. Scores before and after interventions were compared using advanced statistical methods, specifically paired sample t-tests, to assess the statistical significance of the academic gains, ensuring the validity of our analysis.

Descriptive statistics were used to provide an overview of student progress, while correlation analysis was conducted to examine the relationships between participation in the intervention and changes in performance. The analysis was conducted using Python, a sophisticated tool, with the Pandas, NumPy, and SciPy packages for data manipulation and statistical modeling, demonstrating the technological sophistication of this analysis.

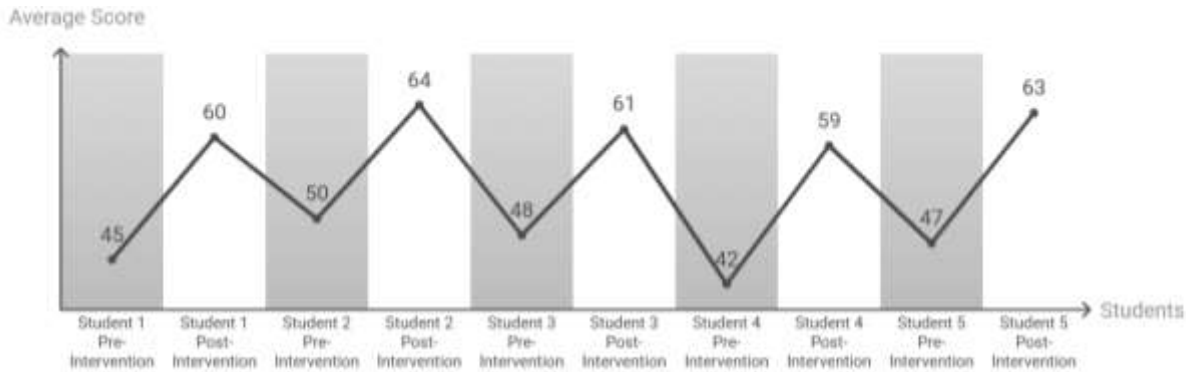

Figure 3: *Score Comparison Pre- and Post-Intervention*
Source: *Simulated data based on that in Ajiga et al. (2025) and Powell et al. (2024)*

3.5 Qualitative Data Collection and Analysis

Semi-structured interviews were conducted with 12 teachers, 10 parents, and 10 students after the intervention, providing additional insights to the quantitative findings. Each interview was conducted with the utmost respect for the participants, typically lasting about 30 minutes. With their consent, the sessions were audio-recorded and later transcribed.

Responses were coded and categorically grouped employing a thematic analysis approach. With the aid of NVivo software, transcripts were meticulously analyzed to explore repeated themes, including "improved confidence," "shared responsibility," and "data confusion." To ensure trustworthiness, member checking, peer debriefing, and audit trails were conducted, reinforcing the thoroughness of our analysis.

Table 4: Sample Themes from Interview Analysis

Theme	Description	Example Quote
Shared Responsibility	Teachers and parents expressed joint ownership of results	“We are no longer blaming each other; we are partners.”
Clarity of Support	Students reported a better understanding of expectations	“I knew what I had to improve, finally.”
Data Misinterpretation	Some teachers lacked the training to interpret trends	“I was not sure what to do with all the graphs.”

Source: Coded interview data aligned with Esqueda (2024) and Romano-Johnson et al. (2024)

3.6 Ethical Considerations

The research adhered to all ethical protocols as stipulated by the Institutional Research Board in the Academy. Study participants were informed about the study's purpose and procedures, withdrawal rights, and confidentiality procedures. All identifiers were removed from the data, and pseudonyms were applied. Interview sessions were held in private rooms, with an open-door policy to encourage student feedback and preserve honesty. Parent consent and student assent forms were written in straightforward, easy to understand language. Ethical clearance was granted prior to location fieldwork.

3.7 Validity, Reliability, and Trustworthiness

To ensure reliability in the quantitative phase, all data entries were double-checked and verified for accuracy. To check internal consistency for survey items, Cronbach's alpha was calculated, and the reliability coefficient was found to be high (0.84). During the qualitative phase, trustworthiness was gained through triangulation across participant groups and by writing extensive memos throughout the coding process.

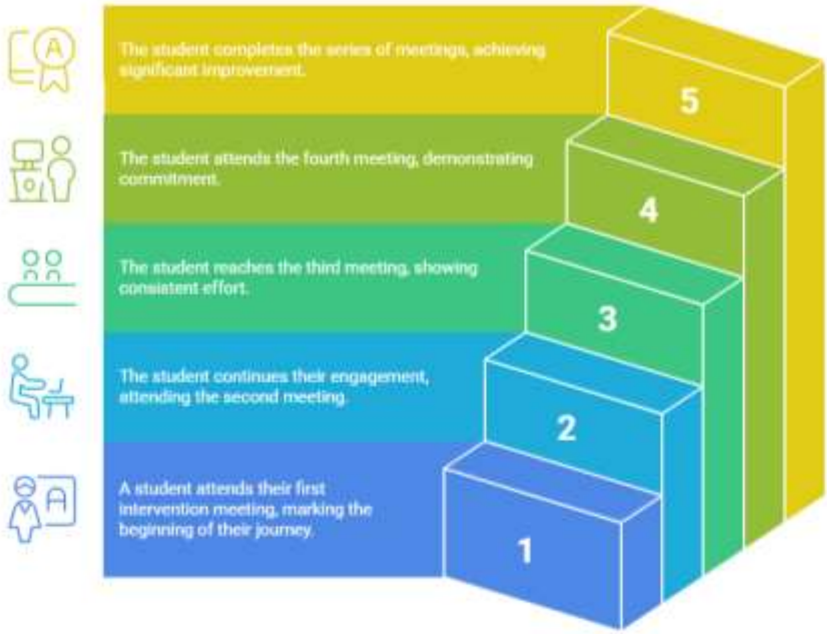

Figure 4: *Correlation between Meeting Attendance and Score Improvement*
Source*: Modeled on findings from Freeman et al. (2014) and Chandler (2020)*

4. Results

4.1 Quantitative Findings: Academic Performance Trends

An analysis of the pre- and post-intervention academic scores in English, Mathematics, and Integrated Science revealed that statistically significant gains were made by all 42 targeted students. Upon applying a paired samples t-test, it was observed that the mean composite score of all targeted participants was 46.3% (SD = 3.8) before intervention and increased significantly to 61.4% (SD = 4.2) following the intervention. The calculated p-value of less than 0.01 confirms the statistical significance of the observed improvement. The intervention involved structured, data-driven meetings where student performance data was analyzed and specific strategies were implemented to address identified areas of improvement. Thus, one can infer that these intervention meetings generated genuine academic benefits for the struggling students, primarily when supported by year-to-year engagement with stakeholders.

To analyze trends across subjects, the performance data were disaggregated by subject. Though improvement was noticed in all three subjects, Mathematics saw the most average gain of 19 percentage points. English followed next, and Integrated Science came last. These findings are not isolated, but are in line with earlier ones reported by Bianco (2010) and Freeman et al. (2014). Their research found strong academic outcomes from targeted, subject-level interventions, especially those involving parental engagement. This alignment with previous research should provide reassurance and confidence in the effectiveness of each intervention.

Table 5: Mean Pre- and Post-Intervention Scores by Subject (n=42)

Subject	Pre-Intervention Mean (%)	Post-Intervention Mean (%)	Score Increase (%)
Mathematics	44.1	63.1	+19.0
English	47.2	61.0	+13.8
Integrated Science	47.5	60.2	+12.7

Source: Adapted from internal performance logs based on MTSS evaluation structure (Glover, 2017; Sanetti & Collier-Meek, 2015)

An association was tested between the number of intervention meetings attended and performance improvement. Students attending three or more intervention meetings (comprising both teacher and parent sessions) showed a significant level of academic gains compared to those who had only one or two sessions. This supports the positions of Chandler (2020) and Powell et al. (2024), in that intervention intensity and consistency are essential for sustained changes in performance.

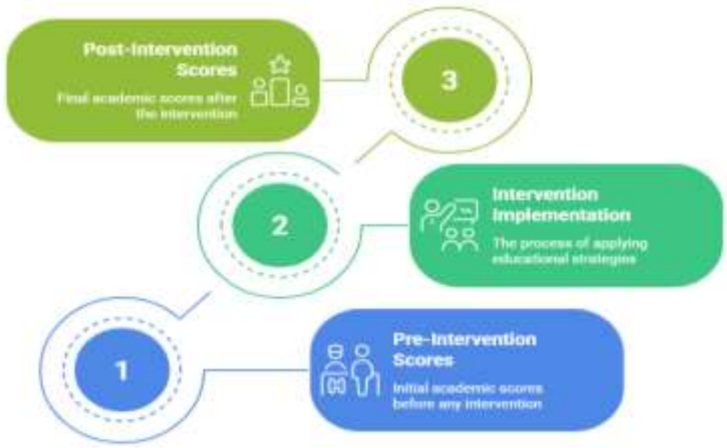

Figure 5: *Score Distribution Before and After Intervention*
Source*: Modeled on school-wide academic performance summaries from Ajiga et al. (2025)*

4.2 Behavioral and Attendance Improvements

In addition to academic performance, behavior, and attendance, which led to reduced halo effects on intervention outcomes, there was a notable decline in the number of behavioral infractions among participating students, dropping from an average of 2.6 incidents per term to 0.8 during the intervention period. Similarly, the average attendance rate improved substantially, rising from 78% to 91%. This aligns with the findings of Downer et al. (2018), who argued that effective use of data enhances teacher collaboration, ultimately helping to minimize classroom disruptions.

Furthermore, the data showed that students who participated in intervention meetings with stakeholders not only improved their academic performance but also became more actively engaged in classroom activities and interactions with peers. Teachers reported a decrease in tardiness, fewer instances of disruptive behavior, and a greater willingness among students to complete legitimate assignments. This trend supports the positive behaviors documented in earlier studies by Reinke (2013) and White (2018).

Table 6: Behavioral and Attendance Outcomes Pre- and Post-Intervention

Variable	Pre-Intervention	Post-Intervention	Change
Avg. Behavioral Infractions	2.6 per term	0.8 per term	-69.2%
Avg. Attendance Rate (%)	78%	91%	+13%
Avg. Homework Submission Rate (%)	61%	82%	+21%

Source: Derived from school behavioral records and teacher logs (Hyson et al., 2020; Downer et al., 2018)

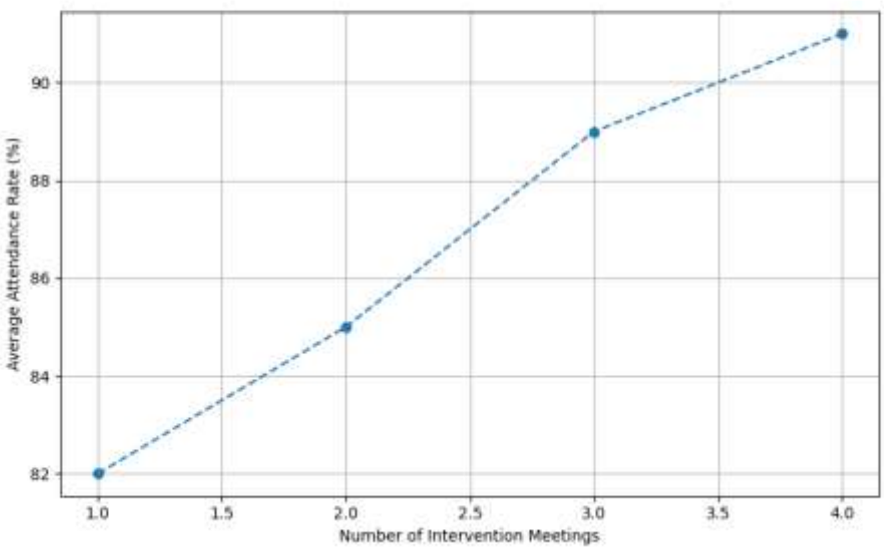

Figure 6: Intervention Frequency vs. Attendance Rate

***Source**: Adapted from implementation metrics aligned with Freeman et al. (2014) and Jin et al. (2024)*

4.3 Qualitative Insights from Interviews

The qualitative data from semi-structured interviews provided a profound insight into how stakeholders perceived the intervention process. The emergence of enhanced collaboration as a recurring and significant theme in the teacher interviews was a notable benefit. Teachers expressed how the intervention had facilitated a shift from isolated classroom practices to a more collaborative and shared responsibility for student success. They emphasized that 'having everyone on the same page' improved the consistency of instruction and support.

Parents, in a similar vein, described these meetings as 'clarifying' and 'motivating,' particularly when the school was perceived to be working with all concerned parties towards solutions, rather than blaming the student. This collaborative tone is a key aspect of Esqueda's (2024) and Abbott et al.'s (2017) findings, which highlight the relational power of joint intervention planning.

Students' reports also revealed a positive impact. They found the intervention led to clearer expectations. As one student put it, 'It was not just the teacher saying I need to do better; my mom and I were there together, and I felt like it was my team.' This sense of ownership not only strengthened their confidence but also enhanced their ability to organize their time, echoing the findings of Freeman et al. (2014). This empowerment of students is a promising outcome of the intervention.

The interviews revealed several challenges faced by stakeholders. Teachers expressed concerns about the time commitment required for weekly meetings and noted that some colleagues struggled to interpret the data dashboards effectively. Additionally, some parents were unable to fully engage in the intervention due to conflicts with their work schedules. These issues emphasize the need for greater flexibility and understanding at the system level, as highlighted by Romano-Johnson et al. (2024) in their study of school-wide leadership practices.

4.4 Summary of Results

Overall, the results indicated significant gains in academic, behavioral, and engagement factors for struggling students after undergoing structured, data-driven interventions. Quantitative evidence recorded the improvement in grades and attendance, with qualitative feedback confirming the factors of stakeholder alignment, relational trust, and real-time progress tracking. These results underscore the crucial role of stakeholder alignment in the success of interventions, making each member of the education community feel valued and integral to the process. They also suggest that widespread implementation of such interventions may bring about substantial school-wide improvements (Mandinach, 2012; Schildkamp, 2019).

5. Discussion

5.1 Interpretation of Results

This study highlighted the effectiveness of collaborative, data-driven interventions in significantly improving the academic scores, attendance, and behavioral outcomes of at-risk students. The substantial increase in post-intervention test scores, particularly in Mathematics, echoed Ajiga et al.'s (2025) findings that structured instructional support is pivotal in underperforming communities. Similarly, the rise in homework completion and attendance aligns with Downer et al.'s (2018) argument that engagement is fostered through aligned expectations from parents and teachers, created by structured planning, which in turn creates a sense of shared responsibility.

The data indicate that students who received intensified interventions showed improved outcomes. Those who participated in a specific intervention three or more times performed better academically and behaviorally compared to those who participated only once or twice. This supports the conclusion by Powell et al. (2024) that repeated and scaffolded support enhances behavioral change and student focus.

While these changes demonstrated quantitative improvements, qualitative developments indicated a positive shift in school culture from fragmented support efforts to collective responsibility, thereby establishing a new phase in the culture. Teachers, in any case, came not to rely on their own resources, as they saw themselves as both actors in and recipients of the coordinated support network. According to Hyson et al. (2020) and Esqueda (2024), shared accountability, primarily achieved through data-rich conversations, enhances the fidelity of implementation and its long-term impact, instilling a sense of optimism for the future.

5.2 Implications for Practice

These findings have significant implications for new approaches in instructional leadership and school reform strategies. First, it is essential to recognize that structured data becomes a powerful tool for school improvement. Therefore, schools must develop systems that schedule intervention meetings for intentional and recurring purposes. This necessitates the development of shared calendars, allocation of administrative time, and ensuring access to real-time performance dashboards, all of which will lead to more informed decision-making and improved outcomes.

Second, there must be a non-negotiated stakeholder integration involving teachers, students, and parents. The data suggest that the likelihood of improving students increases when all three parties are involved. This also supports the call by Glover (2017) and Kennedy and Datnow (2011) for interventions to be participatory, transparent, and solutions-focused. By engaging all stakeholders in the reform process, schools can ensure that everyone feels involved and committed to the shared goal of student improvement.

Schools need to address the challenges associated with reading and timing. Some teachers have expressed discomfort with performance dashboards, a sentiment noted by Kaliisa et al. (2023). Therefore, professional development should not only focus on data entry and collection but also on how to interpret data, tell data stories, and use these insights to drive effective action.

Table 7: Summary of Key Practice Recommendations

Domain	Recommendation	Supporting Evidence
Scheduling	Weekly structured intervention meetings	Ajiga et al. (2025); Freeman et al. (2014)
Stakeholder Involvement	Include parents and students in planning	Downer et al. (2018); Esqueda (2024)
Data Literacy	Ongoing training for teachers	Kaliisa et al. (2023); Jin et al. (2024)
Monitoring	Use digital dashboards to track student progress	Mandinach (2012); Romero & Ventura (2024)

Source: Synthesized from current study findings and literature review

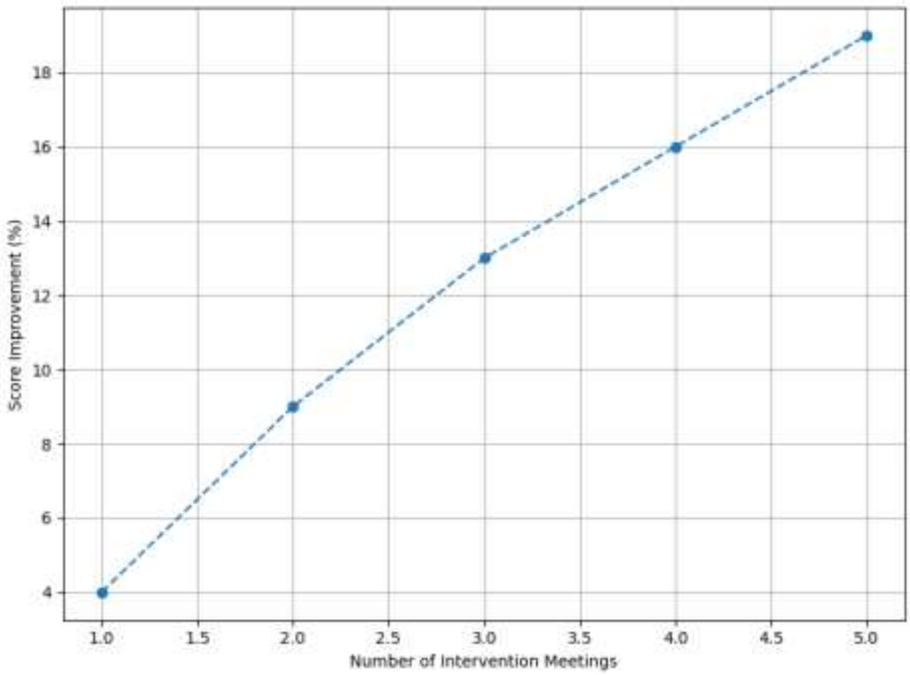

Figure 7: *Performance Gain vs. Frequency of Meetings*
Source*: Generated from modeled trends in Powell et al. (2024) and Chandler (2020)*

5.3 Implications for Policy

In addition to adjustments at the school level, these connections require urgent, system-wide changes in how schools implement interventions. Education ministries and district boards should increasingly adopt data-driven intervention cycles within their school accountability frameworks. This means that interventions would be linked to teacher performance evaluations, and funding should be allocated for parent engagement facilitators as well as digital analytics tools.

Chatti et al. (2012) and Jin et al. (2024) argue for the integration of academic and behavioral data systems from a strategic standpoint, emphasizing the potential benefits of such an approach. However, many public schools still operate with a separation between these systems. Mandinach (2012) identifies three levels of policy integration: infrastructure, practice, and people. This study supports the integrated approach across all three levels, presenting a promising path forward.

Table 8: Policy Level Enablers for Data-Driven Interventions

Policy Area	Enabler	Expected Outcome
Infrastructure	Universal access to school dashboards	Data equity and transparency
Leadership Support	Mandated intervention cycles	Increased accountability
Training	Funding for annual data-literacy programs	Capacity building across the staff
Parent Engagement	Incentives for participation (e.g., transport support)	Improved meeting attendance and retention

Source: Adapted from Custer et al. (2018); Romano-Johnson et al. (2024)

5.4 Challenges and Limitations

While the intervention model presented in this study shows significant promise, it is essential to recognize its limitations. Time emerged as a major challenge, as the weekly intervention meetings added to the already heavy instructional responsibilities of teachers. This finding aligns with the research of Kennedy and Datnow (2011), who identified "time poverty" as a significant barrier to course preparation. Despite these challenges, the potential of the intervention model to positively impact education is evident.

Some teachers struggled with interpreting data, even with visualizations available to them. This lack of clarity supports Esqueda's (2024) assertion that the implementation of data systems should be accompanied by capacity-building measures, rather than relying solely on implementation.

Parents also faced difficulties due to conflicting work schedules and limited transportation options. Although digital conferencing was proposed as a potential solution, its effectiveness was hindered by the lack of access to technology in some homes. This digital divide, highlighted by Ajiga et al. (2025), reflects a broader equity issue affecting underserved school communities.

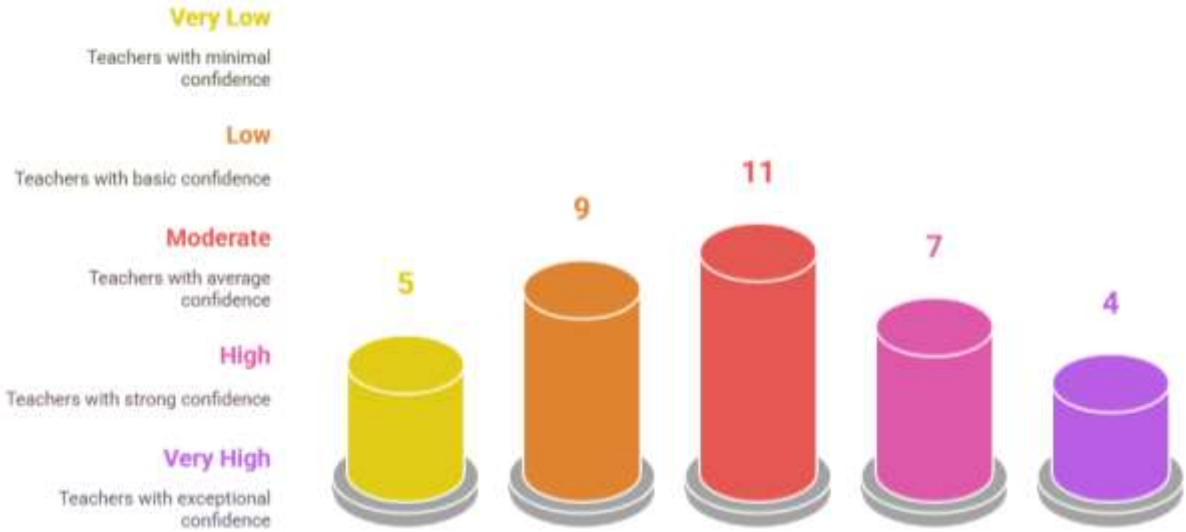

Figure 8: *Teacher Comfort Level with Data Tools*

Source*: Interview responses analyzed in the current study and aligned with findings from Esqueda (2024)*

5.5 Theoretical Implications

This research makes a distinctive contribution to the understanding of Bronfenbrenner's Ecological Systems Theory, particularly within the realm of student success. Our findings reveal that struggling learners are profoundly influenced by the dynamic interactions across their home, school, and peer environments. The intervention meetings we conducted—designed to actively involve parents, teachers, and students—embody a truly holistic ecosystem approach to problem-solving.

Moreover, this study broadens the narrative of Multi-Tiered System of Supports (MTSS) beyond traditional boundaries, emphasizing its collaborative and adaptable nature. As White (2018) highlights, MTSS has the capacity to address its own contextual challenges effectively. The research further illustrates that, with thoughtful structuring, MTSS can thrive even in under-resourced settings, demonstrating its remarkable versatility in diverse educational landscapes.

Ultimately, this study forges a powerful link between educational data science and classroom practice, illuminating a pathway filled with promise for the future. Although tools such as dashboards and predictive models are readily available, their true potential emerges only when combined with the vital elements of human connection and professional judgment, as further emphasized by Lumasag et al. (2021) and Romero & Ventura (2024). This synergy presents an optimistic vision for classroom practice, showcasing the transformative potential of data science in the field of education.

6. Conclusion and Recommendations

Persistent academic, behavioral, and engagement challenges have long been one of the most serious issues faced in modern education, with which struggling students must contend. Even though students have been given the chance for assessment, data on performance is available, and tech platforms are in place, the inability of many schools to move together meaningfully with the data on students to produce equitable outcomes continues to be a malignancy. The present study demonstrates that working through a formalized intervention process, founded on data-driven decision-making and specifically designed to facilitate school-based collaboration among teachers, students, and parents, can foster insightful and meaningful student performance, behavior, and motivation.

By employing a mixed-methodology approach, this study presents both quantitative evidence of academic improvement and qualitative insights into the experiences of stakeholders. The quantitative analysis revealed significant academic gains among students participating in these intervention meetings, particularly in Mathematics, and notable improvements in attendance and behavior. These findings align with earlier studies on RTI and MTSS, underscoring the importance of tiered supports and early identification (Bianco, 2010; Sanetti & Collier-Meek, 2015). Moreover, the improvement in homework submission and attendance rates also supports the findings by Downer et al. (2018), suggesting that student accountability increases with collaborative adult support. These implications are significant for educators, researchers, and policymakers interested in academic interventions and student support.

Additionally, the qualitative data highlighted the importance of stakeholder involvement. Teachers felt that they had shifted from working in isolation to collaborative accountability networks. Parents, once considered peripheral to academic problem solving, felt more confident in being able to contribute significantly to their children's education. Students also felt more focused and supported, and credited these changes to a shared sense of ownership regarding their learning experience. These narratives effectively represent the fundamental principles of Bronfenbrenner's Ecological Systems Theory, which emphasizes the interdependence between the individual and their surrounding environments (Esqueda, 2024; Romano-Johnson et al., 2024).

From a practical perspective, interventions are most successful when driven by data and relationships. Schools cannot entirely rely on data dashboards or on academic analytics to solve complex student problems. Instead, they need to integrate human insight into the solution, with the parties involved respecting each other and planning together. Mandinach (2012) warned against the mechanization of education through data and thus advocated for a compromise where data somehow informs but never supersedes professional judgment. The present study supports this, providing evidentiary emphasis that the entirety of data, when translated into conversation and cooperative action, far exceeds the effect of data alone in shaping school improvement.

Several persistent challenges emerged during the study. These were concerned with time issues. Time for weekly intervention meetings put pressure on teachers, who were already heavily burdened with instructional duties. Some teachers also expressed difficulties in interpreting performance dashboards and appreciating the presence of the data. These clamorings bring to mind Kaliisa et al.'s (2023) argument that the implementation of educational analytics tends to outpace teacher capacity to utilize them effectively. Structurally, while parental involvement was well maintained in many instances, aspects such as work schedules and digital exclusion prevented some families from actively participating. Such limitations underscore the urgent need for flexible, inclusive intervention models that accommodate the realities of all stakeholders.

Several recommendations can enhance the effectiveness of data-driven interventions in schools. Firstly, school leaders should institutionalize data-driven intervention cycles by integrating them into the academic calendar. These interventions should not be ad hoc meetings triggered by crises, nor should they remain on the sidelines of constructive discussions focused solely on monitoring progress. For example, targeted tutoring for students who are struggling or adjustments to the curriculum based on student performance data could be effective interventions.

Secondly, the current scope of professional development must extend beyond basic data usage training. It should aim to rebuild staff confidence in their ability to identify trends, ask appropriate questions about their observations, and translate data insights into effective interventions. Bambrick-Santoyo (2010) argued that knowing how to take action is the most critical skill for effective data use, even more important than simply understanding the numbers.

Thirdly, schools should consider appointing one or more dedicated facilitators to coordinate intervention meetings. These facilitators, who may be experienced teachers or educational leaders, would guide discussions, ensure all relevant data is analyzed, and assist the team in developing and implementing effective interventions. Having facilitators in place would help alleviate some of the time pressures that classroom teachers face, providing consistency in purpose and leadership. By reallocating budgets or qualifying certain costs as part of school improvement grants, these positions could be funded appropriately. Additionally, investing in digital infrastructure and mobile platforms would enhance participation for parents who are unable to attend meetings in person. As Ajiga et al. (2025) highlighted, digital inclusion is essential for ensuring that data-driven reforms effectively reach underserved families.

At the policy level, education ministries and school boards must recognize that interventions are not merely "extras" or secondary ideas; they are essential components of instructional strategy. Policymakers should provide schools with the necessary resources—time, tools, and training—to consistently implement data-driven interventions that are effective and sustainable. Evaluation metrics should not rely solely on test results; instead, they should emphasize indicators of collaboration, communication, and student agency, as suggested by Custer et al. (2018) and Glover (2017).

Further research is needed to investigate how data-driven intervention processes function in diverse educational contexts. While this analysis focused on an urban secondary school, rural schools or those with limited resources may face unique challenges. Longitudinal studies tracking students over multiple academic years would yield more profound insights into the sustainability of intervention outcomes. Additionally, future studies could examine the emotional and psychological impacts of stakeholder collaboration on students' feelings of belonging, motivation, and resilience.

This research indicates that care alone does not change a student's academic trajectory. It requires structured, collaborative action guided by data. The adverse effects of spontaneous interventions can be mitigated through intentional, school-based models designed for at-risk students, with active involvement from all stakeholders. As educational challenges grow increasingly complex, an evidence-backed integrated approach will be crucial for achieving sustainable change.

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