Examining Benchmark Growth Within MTSS in a K-12 Cyber Program: A Quasi Experimental Case Study Comparing In-Person and Virtual WIN Delivery Model

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Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

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Abstract

Examining Benchmark Growth within MTSS in a K-12 Cyber Program: A Quasi-Experimental Case Study Comparing In-Person and Virtual WIN Delivery Models

Multi-Tiered Systems of Supports (MTSS) provide a structured framework for identifying and addressing students' academic needs through data-driven interventions. While MTSS has been widely implemented in traditional school settings, limited research has examined its effectiveness within cyber education environments. The purpose of this applied research study was to examine academic growth within a K-12 cyber program implementing an MTSS framework and to compare the effectiveness of two intervention delivery modalities: in-person WIN (What I Need) sessions and virtual WIN sessions delivered through Microsoft Teams. This study used a quantitative quasi-experimental design with Renaissance STAR Benchmark assessment data collected in August and January. Student growth was measured by changes in STAR scale scores across the testing windows. Paired samples t-tests revealed statistically significant academic growth across the sample, while independent samples t-tests indicated no statistically significant differences between students receiving in-person and virtual WIN interventions. These findings suggest that structured MTSS intervention systems in cyber programs can support student academic growth, and that virtual intervention delivery may provide outcomes comparable to in-person support.

Dedication

This dissertation is dedicated to my family, friends, and loved ones whose encouragement and support made this journey possible and who have learned that my journeys, academic and otherwise, tend to follow the scenic route, and to the educators who remain committed to doing what is best for kids.

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List of Abbreviations

CSP	Culturally Sustaining Pedagogy
ESSA	Every Student Succeeds Act
FERPA	Family Educational Rights and Privacy Act
LMS	Learning Management System
MLL	Multilingual Learner
MTSS	Multi-Tiered System of Supports
PA I-MTSS	Pennsylvania Integrated Multi-Tiered System of Supports
PBIS	Positive Behavioral Interventions and Supports
PDE	Pennsylvania Department of Education
RTI	Response to Intervention
SEL	Social-Emotional Learning
STAR	Standardized Test for the Assessment of Reading and Mathematics
WIN	What I Need (Intervention Block)

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Chapter 1

Introduction

Overview

The expansion of cyber education transformed how K-12 schools delivered instruction, assessed learning, and provided student support. As districts continued to offer full-time and hybrid virtual options, ensuring equitable and responsive systems of support for all learners became a central priority. The Multi-Tiered System of Supports (MTSS) framework, traditionally designed for in-person environments, offered a structure for identifying academic, behavioral, and social-emotional needs through data-driven decision making. However, transferring this model into a cyber setting presented unique challenges. Virtual schools navigated barriers such as limited face-to-face interaction, inconsistent student engagement, and reduced opportunities for real-time observation of learning and behavior.

This quantitative research study explored how a K-12 cyber program strengthened the implementation of MTSS to promote equity, improve consistency, and ensure timely intervention for all students. Drawing from the implementation of culturally sustaining practices, this study aimed to develop actionable recommendations that improved how online educators, administrators, and families collaborated to meet student needs within a digital environment.

Background

The MTSS framework emerged from decades of research on early intervention, inclusive education, and systems-level problem solving. Initially rooted in Response to Intervention (RTI), an instructional model designed to identify academic needs early and provide tiered, data-based supports, and Positive Behavioral Interventions and Supports (PBIS), a proactive, schoolwide approach focused primarily on improving behavior and school climate, MTSS evolved into a comprehensive structure addressing academic, behavioral, and social-emotional domains through a tiered model of support. At its foundation, MTSS emphasized prevention and early identification, ensuring that all students received high-quality instruction with access to progressively intensive support as their needs increased.

While MTSS was well established in traditional brick-and-mortar schools, its implementation in online environments remained inconsistent. Cyber programs, particularly those that served a broad range of students across multiple districts, faced distinctive barriers. Teachers often juggled asynchronous communication, diverse student schedules, and variations in parental involvement. Additionally, many online platforms were not designed for seamless progress monitoring or behavioral data collection, creating gaps in tier identification and intervention fidelity. This challenge was well documented in virtual learning environments where data fragmentation and limited real-time visibility hindered effective MTSS implementation (Evans et al., 2022; Guest et al., 2024).

Research emphasized that strong MTSS frameworks depended on collaboration, consistent data use, and culturally responsive practices (Freeman-Green et al., 2021; Sugai & Horner, 2020). Yet, these pillars were often difficult to uphold virtually. For example, Evans et al. (2022) found that fewer than 30% of cyber programs reported having a fully implemented MTSS system, citing challenges in data collection, staffing, and communication. These realities underscored the need for adaptive models that maintained the fidelity of MTSS while honoring the flexibility and accessibility that defined cyber learning.

This study examined the intersection between digital learning and systems of support. By identifying both barriers and opportunities within one established K-12 cyber program, it aimed to contribute to the broader understanding of how MTSS could be effectively adapted to virtual settings without compromising its core principles.

Problem Statement

Although MTSS had been shown to improve academic and behavioral outcomes when implemented with fidelity, many cyber programs struggled to operationalize its components consistently across virtual platforms. A lack of standardized systems limited real-time observation, and uneven collaboration among teachers and support staff often resulted in delayed interventions and inequitable access to resources. These inconsistencies disproportionately affected students requiring targeted or intensive support, particularly those with disabilities, multilingual learners, or students from economically disadvantaged backgrounds.

The problem guiding this study was that MTSS implementation in cyber education settings lacked consistency, equity, and culturally responsive adaptation, which limited the effectiveness of support for diverse learners. Without intentional redesign, virtual programs risked widening achievement and engagement gaps that MTSS was originally designed to close.

Purpose of the Study

The purpose of this applied research study was to examine the current state of MTSS implementation within a K-12 cyber program and to identify practical strategies for enhancing equity, fidelity, and sustainability. This study sought to determine how educators integrated culturally sustaining practices and data-informed decision-making into a virtual environment while maintaining strong collaboration across roles.

Through this investigation, the researcher aimed to develop actionable recommendations to improve MTSS delivery within the cyber program. These findings were intended to support not only local practice but also to provide guidance for other districts and cyber schools seeking to strengthen their virtual intervention systems.

Significance of the Study

This study held theoretical, empirical, and practical significance. Theoretically, it extended the application of MTSS beyond traditional school walls into a fully virtual learning environment. By aligning implementation with Culturally Sustaining Pedagogy (CSP), this research examined how MTSS could evolve to meet the needs of diverse cyber learners while honoring students' identities, languages, and lived experiences. CSP, as conceptualized by Paris and Alim (2017), provided the cultural and equity-oriented lens for this study, emphasizing that interventions must sustain, rather than simply acknowledge, students' cultural ways of being. To guide the structural and instructional components of MTSS, this study drew on an established MTSS framework commonly represented as an inverted pyramid, which positioned Tier 1 universal instruction as the broadest foundation, Tier 2 targeted intervention as the middle tier, and Tier 3 intensive supports at the narrowest point (Haring Center for Inclusive Education & OSPI, 2020). This inverted tier model was frequently used in professional development literature, including works such as *Explicit Instruction: Effective and Efficient Teaching* (Archer & Hughes, 2011), which outlined essential features of Tier 2 intervention design.

Together, CSP and the inverted MTSS framework formed the theoretical underpinnings of this study. CSP provided the rationale, ensuring that MTSS practices in cyber environments remained equitable, identity-affirming, and responsive, while the inverted MTSS model provided the structure, offering a structured, evidence-based approach to Tier 2 instruction, intervention fidelity, and data-driven decision making within virtual learning systems. This dual framework foundation situated in the study at the intersection of cultural responsiveness and systems-level improvement, reflecting how MTSS needed to adapt alongside technology and evolving educational landscapes.

Empirically, this study contributed to a limited but growing body of literature addressing MTSS in cyber and hybrid programs. Much of the existing research focused on brick-and-mortar implementation, leaving a need for applied studies that examined MTSS effectiveness, barriers, and opportunities within online contexts.

Practically, the study provided school leaders, teachers, and support staff with concrete recommendations for improving collaboration, intervention fidelity, and student monitoring in virtual settings. These insights had the potential to enhance not only student outcomes but also teacher confidence and family engagement in cyber programs. The study's findings could inform professional learning, district policy, and system-level decision making as virtual learning continued to expand across Pennsylvania and beyond.

Research Questions

This applied research study was guided by two primary research questions that examined student academic growth within a cyber education setting and evaluated the effectiveness of targeted intervention delivery models within a Multi-Tiered System of Supports (MTSS) framework.

Research Question 1 focused on overall academic growth among students enrolled in the cyber program, as measured by the Renaissance STAR Benchmark assessment from August to January. This question was designed to determine whether students demonstrated measurable academic progress during the first semester of enrollment in a fully online instructional environment.

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Research Question 2 examined whether differences existed in academic growth outcomes between students receiving in-person WIN (What I Need) intervention support and those receiving virtual WIN support. By comparing growth across these two MTSS delivery modalities, this study sought to identify whether the mode of intervention delivery was associated with differential student outcomes.

Collectively, these research questions supported the overarching goal of informing evidence-based MTSS implementation in cyber education by evaluating both overall student growth and the relative effectiveness of intervention modalities. Findings from this study aimed to provide practical guidance for designing equitable, responsive, and data-informed MTSS structures that met the diverse academic needs of students in a virtual learning environment.

Definition of Terms

Multitiered System of Supports (MTSS). A comprehensive, tiered framework that integrates academic, behavioral, and social emotional support through databased decision making.

Response to Intervention (RTI). A tiered instructional framework focused on early identification and support of students with academic needs through research-based instruction, frequent progress monitoring, and data-driven decision-making.

Positive Behavioral Interventions and Supports (PBIS). A proactive, schoolwide framework that uses explicit behavior expectations, prevention strategies, and data-based interventions to improve student behavior, school climate, and social-emotional functioning.

Cyber School. A fully virtual or hybrid K-12 educational program where students attend classes online in whole or in part.

Tiered Interventions. Structured levels of support that increase in intensity, ranging from universal (Tier 1) to targeted (Tier 2) and individualized (Tier 3).

Culturally Sustaining Practices. Instructional and support strategies that affirm students' cultural identities and promote equity within the learning environment.

Virtual Collaboration. The use of online tools and platforms to facilitate communication and shared decision making among educators, students, and families.

Implementation Fidelity**.** The degree to which MTSS practices are executed as designed to ensure consistency and accuracy of interventions.

Delimitations

This study focused on a Pennsylvania-based K-12 cyber program. The scope included staff perceptions and structural analysis of MTSS practices rather than longitudinal student outcomes. Findings were contextualized within this cyber program's model and were intended to inform practical improvement rather than to generalize across all virtual schools.

Summary

This chapter introduced the growing importance of MTSS in cyber education and outlined the challenges and opportunities that existed within virtual implementation. It defined the problem, clarified the study's purpose, and highlighted its significance from multiple perspectives. The chapter concluded with the research questions that guided the investigation.

Chapter Two provided a comprehensive review of literature related to MTSS implementation, emphasizing its theoretical foundations, historical development, and emerging adaptations for virtual education. The review also explored the integration of culturally sustaining practices within online frameworks to strengthen equity and responsiveness across tiers of support.

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Chapter 2

Literature Review

Overview

This chapter reviewed current research and foundational theory related to the Multi-Tiered System of Supports (MTSS), emphasizing its adaptation within cyber education. The review examined how MTSS had evolved as a framework for equitable student support, explored its theoretical underpinnings, and synthesized literature on implementation challenges, culturally sustaining practices, and virtual adaptations. The goal was to situate this study within the context of contemporary educational systems while identifying the knowledge gaps this research addressed.

Theoretical Framework

The MTSS framework aligned closely with two theoretical strands that informed this study: Implementation Science and Culturally Sustaining Pedagogy. Together, they provided both a process and a purpose for improving equity-focused systems of support in cyber programs.

Implementation Science offered a structured approach to translating theory into practice. It emphasized fidelity, sustainability, and contextual adaptation when new frameworks, such as MTSS, were introduced (Fixsen et al., 2019). Implementation Science was defined as the systematic study of methods and strategies that supported the effective adoption, integration, and scale-up of evidence-based practices within real-world settings. Within a virtual environment, this theory underscored the need for clearly defined systems, purposeful training, and robust digital progress-monitoring tools that ensured interventions remained consistent and effective despite limited physical proximity and the unique complexities of online learning.

Culturally Sustaining Pedagogy (CSP), advanced by Paris and Alim (2017), focused on affirming students' cultural identities and integrating these perspectives into curriculum and support systems. Embedding CSP within MTSS ensured that academic, behavioral, and social-emotional interventions respected students' lived experiences, particularly in diverse digital learning communities. When viewed together, Implementation Science guided the *how* of MTSS, while Culturally Sustaining Pedagogy defined the *why*, creating an inclusive framework that honored both fidelity and identity.

Historical Context of MTSS

MTSS emerged from decades of reform focused on early intervention and inclusive education. Its origins traced to two major movements: Response to Intervention (RTI) and Positive Behavioral Interventions and Supports (PBIS).

MTSS developed from several decades of educational reform aimed at improving outcomes for diverse learners through early identification, prevention, and inclusive practices rather than reactive or exclusionary models of support. Prior to the development of MTSS, student difficulties were often addressed through a wait-to-fail approach, in which academic or behavioral concerns were not formally addressed until students demonstrated significant and persistent failure. This model disproportionately impacted students with disabilities, multilingual learners, and students from historically marginalized backgrounds, as supports were frequently delayed, fragmented, or tied to categorical labels rather than demonstrated need.

Beginning in the late twentieth century, federal and state reform movements increasingly emphasized early intervention and accountability for all learners. The reauthorization of special education legislation, along with broader standards-based reform efforts, shifted the focus toward ensuring access to high-quality instruction within general education settings. During this period, initiatives such as Reading First, schoolwide prevention models, and the growing use of curriculum-based measurement promoted the idea that instructional response, rather than student deficit, should guide decision making. These reforms laid out the groundwork for Response to Intervention (RTI), which emphasized universal screening, tiered instruction, and progress monitoring to identify students at risk and provide timely support.

As understanding student needs expanded beyond academics, MTSS evolved as a more comprehensive framework that integrated academic, behavioral, and social-emotional support within a unified system. Influenced by Positive Behavioral Interventions and Supports (PBIS), implementation science, and equity-focused reform, MTSS moved beyond intervention alone to emphasize strong Tier 1 instruction, data-driven problem solving, and inclusive service delivery. This shift reflected a growing recognition that student success was shaped by instructional quality, school climate, cultural responsiveness, and systemic coherence. Within this historical context, MTSS represented the culmination of reform efforts designed to ensure that all students, regardless of background or learning profile, received timely, equitable, and effective support within a shared educational framework.

Response to Intervention (RTI)

Developed in the early 2000s, RTI was an instructional framework designed to identify and support students with academic difficulties through a tiered system of increasingly intensive interventions (Fuchs & Fuchs, 2006). The core RTI principles included the following.

Response to Intervention (RTI) was a prevention-oriented framework designed to provide early, systematic academic support to students before learning difficulties became entrenched. At the foundation of RTI was Tier 1, which consisted of high-quality core instruction delivered to all students. High-quality Tier 1 instruction was characterized by standards-aligned curriculum, research-based instructional practices, clear learning objectives, frequent formative assessment, and differentiated instructional strategies that addressed a range of learner needs within the general education setting. Instruction at this level was delivered by highly qualified educators and was responsive to student data, with the expectation that most students (typically 80-85%) would demonstrate adequate progress when Tier 1 instruction was effective.

A central component of RTI was universal screening, which was used to identify students who might be at risk for academic difficulty. Students were considered "at risk" when screening data indicated performance below established benchmarks or expected levels of proficiency for their grade or age. Universal screeners were administered to all students multiple times per year and served as an early warning system, allowing educators to identify potential concerns before they resulted in significant academic gaps. Importantly, identification of risk was based on data patterns rather than labels, ensuring that students received timely support without unnecessary delay or stigma.

Students identified as at risk through universal screening and classroom data received Tier 2 targeted, evidence-based interventions. These interventions were typically delivered in small groups and focused on specific skill deficits, such as foundational literacy or numeracy skills, using instructional approaches that had demonstrated effectiveness through empirical research. Tier 2 interventions were provided in addition to, not in place of, core instruction and were implemented with increased intensity, structure, and instructional time. Interventionists included classroom teachers, reading specialists, intervention teachers, or other trained staff, depending on school structures and resources.

Frequent progress monitoring was used to assess students' responsiveness to intervention and to inform instructional adjustments. Progress monitoring tools were brief, reliable measures aligned with the targeted skills being addressed and were administered on a regular basis, often weekly or biweekly at Tier 2. Classroom teachers and interventionists were responsible for collecting and recording progress data, which were then summarized and shared through data dashboards, progress reports, or MTSS documentation systems. At Tier 1, progress monitoring took the form of formative classroom assessments and benchmark data reviews, while at Tier 3, monitoring occurred more frequently and with greater individualization.

Decisions regarding movement between tiers were made collaboratively through a data-based problem-solving process. MTSS or RTI teams, often composed of classroom teachers, interventionists, special educators, administrators, school psychologists, and support staff, met regularly to review student data, evaluate intervention fidelity, and determine next steps. These teams considered multiple data sources, including screening results, progress monitoring trends, classroom performance, and intervention implementation data. Decisions to intensify, fade, or discontinue interventions were guided by documented student response rather than predetermined timelines, ensuring that instructional support remained flexible, responsive, and grounded in evidence. Through this team-based, data-informed approach, RTI functioned as a proactive system designed to support student success early and equitably.

Positive Behavioral Interventions and Supports (PBIS)

PBIS is a proactive, schoolwide framework aimed at improving student behavior, social-emotional functioning, and overall school climate (Sugai & Horner, 2002). Key PBIS principles include the following:

Explicit teaching of behavioral expectations,

Consistent reinforcement systems that encourage positive behaviors, Predictable routines and procedures,

Use of behavioral data to guide interventions and decision-making, and

Tiered behavior supports students needing additional intervention.

PBIS emphasizes prevention, consistency, and environmental design to reduce challenging behavior and increase engagement.

Integration into MTSS

Over time, educators recognized that separating academic and behavioral interventions limited effectiveness. MTSS unified these models, integrating academic, behavioral, and social-emotional supports into a single, holistic system grounded in prevention, early identification, and tiered intervention (Freeman-Green et al., 2021). This evolution reflected a broader shift toward systems thinking, emphasizing data use, collaboration across disciplines, and the need to meet the academic, behavioral, and social-emotional needs of the "whole child."

MTSS served as a framework for continuous improvement and equity. Nationally, the adoption of the Multi-Tiered System of Supports (MTSS) was driven by persistent achievement and discipline gaps, inconsistent intervention practices, and the limitations of maintaining separate academic (RTI) and behavioral (PBIS) systems. With the passage of the Every Student Succeeds Act (ESSA, 2015), states were encouraged to implement evidence-based frameworks that prioritized early intervention, data-driven decision-making, and whole-child supports-conditions that aligned closely with MTSS principles. As a result, more than 86% of states incorporated MTSS in their State Systemic Improvement Plans, using the model to advance prevention, equity, cross-disciplinary collaboration, and systemic coherence (States of I-MTSS Brief, 2024; NEA, n.d.).

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In Pennsylvania, MTSS was formally adopted as Pennsylvania's Integrated MTSS (PA I-MTSS) to address similar systemic needs, including reducing disproportionate outcomes, strengthening inclusive education, and ensuring that all students had access to high-quality core instruction and tiered supports. PA I-MTSS was defined by the state as a "standards-aligned, comprehensive school improvement framework" that integrated academic, behavioral, and social-emotional supports, emphasizing universal screening, data-based decision-making, and shared leadership structures to promote continuous improvement and equity across the K-12 system (PaTTAN, n.d.; West Shore School District, n.d.). Together, the national and Pennsylvania frameworks reflected a broader movement toward coherent, equitable, and prevention-oriented systems that supported students holistically. MTSS was embedded within state standards and school improvement planning, reflecting ongoing efforts to align instruction, intervention, and assessment under a unified model of support.

Core Components of MTSS

Successful MTSS frameworks share several defining components that function collectively to provide equitable student support:

Tiered Continuum of Support

MTSS organizes interventions into three tiers:

Tier 1**:** Universal support provided to all students through high quality, research-based instruction.

Tier 2**:** Targeted interventions for students who need additional support beyond the core curriculum.

Tier 3**:** Intensive, individualized interventions addressing significant academic or behavioral needs (Berkeley et al., 2020).

The tiered approach allowed educators to respond systematically to student data, ensuring that support increased intensity as needed without waiting for failure to occur.

Successful MTSS frameworks were grounded in a tiered continuum of support designed to deliver instruction and intervention with increasing levels of intensity based on student need.

This structure ensured that all students received appropriate support in a timely manner and that instructional decisions were driven by data rather than delayed identification or failure. Each tier served a distinct purpose within the system while remaining interconnected and fluid, allowing students to move between levels as their needs changed.

Tier 1 represented the foundation of MTSS and consisted of high-quality, research-based instruction provided to all students within the general education setting. Instruction at this level was standards-aligned, culturally responsive, and was delivered by general education teachers using evidence-based instructional practices. Tier 1 instruction included clear learning objectives, explicit teaching, opportunities for guided and independent practice, and ongoing formative assessment. Universal screening and classroom-level data were used to evaluate the effectiveness of Tier 1 instruction as a whole, with the expectation that the majority of students would meet grade-level benchmarks when core instruction was strong. When a significant proportion of students did not demonstrate adequate progress, instructional adjustments were made at the Tier 1 level before individual students were considered for additional intervention.

Tier 2 provided targeted interventions for students who did not demonstrate sufficient progress with Tier 1 instruction alone. Placement into Tier 2 was determined through a data-based problem-solving process that included review of universal screening results, classroom performance, and other relevant data sources. Instruction at Tier 2 was more focused and intensive, typically delivered in small groups and designed to address specific skill deficits identified through assessment data. These interventions were evidence-based, time-bound, and were provided in addition to, not in place of, core instruction. Tier 2 instruction was delivered by classroom teachers, interventionists, reading or math specialists, or other trained staff, depending on school resources and structures. Student progress was monitored regularly to determine responsiveness and to inform instructional adjustments.

Tier 3 consisted of intensive, individualized interventions for students with significant and persistent academic or behavioral needs. Students were considered for Tier 3 when data indicated minimal or insufficient response to Tier 2 supports. Instruction at this level was highly individualized, often delivered one-on-one or in very small groups, and might involve increased instructional time, specialized strategies, or alternative instructional approaches. Tier 3 interventions were typically implemented by specialized staff, such as intervention specialists, special educators, or related service providers, and were closely monitored using frequent progress monitoring measures. Data from Tier 3 interventions were used not only to guide instructional decisions but also to inform potential referrals for special education evaluation when appropriate.

Across all tiers, decisions regarding placement, movement, and instructional intensity were made collaboratively by MTSS teams composed of educators, specialists, and administrators. This team-based approach ensured consistency, fidelity, and equity in implementation. By organizing instruction within a tiered continuum, MTSS enabled schools to respond systematically to student needs, increase support proactively, and provide equitable access to effective instruction without relying on a wait-to-fail model (Berkeley et al., 2020).

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Data Driven Decision Making

Frequent data collection is integral to a tiered support framework summative, formative, and collective assessments each play distinct roles in guiding instruction, tier placement, and system improvement (Al Otaiba et al., 2019).

Summative Data

These were periodic benchmark assessments (e.g., fall, winter, spring universal screeners) used across a grade level or schoolwide to evaluate broad instructional effectiveness and curriculum alignment. When summative data revealed patterns, such as a high percentage of students performing below benchmark, instructional leaders and curriculum teams responded by reviewing and revising the Tier 1 core curriculum (e.g., pacing, scope and sequence, alignment with standards). For example, if the August universal screener showed that 40% of students in Grade 4 failed to meet expectations in number sense, the district revised the Tier 1 math program to include more foundational number sense content and professional development for teachers.

Formative/Classroom Data

These data were gathered more frequently (weekly or biweekly) and included teacher-designed exit tickets, daily observations, small-group checklists, and progress-monitoring probes. Formative data informed decisions about which students needed Tier 2 support, what specific skill deficits existed, and how instructional groups should be structured. When a teacher identified a cluster of students missing two or more proficiency markers in decoding after three weeks of instruction, those students were moved into a targeted Tier 2 small-group intervention focused on decoding and fluency. Teachers or interventionists monitored student responses weekly and adjusted grouping, content, or pacing as needed.

Collective/Collaborative Data Review

This process occurred when MTSS teams or data teams analyzed sets of formative and summative data to determine system-wide trends, intervention fidelity, resource allocation, and equity considerations. For example, if progress-monitoring data indicated that students from a specific demographic group consistently showed slower response rates in Tier 2, the team investigated cultural or accessibility factors, adjusted intervention materials, or delivered targeted professional development on culturally sustaining practices. Collective data review also helped determine when students should transition between tiers; students who failed to show satisfactory growth in Tier 2 after a predetermined number of sessions were considered for Tier 3, and the decision was documented in system records.

Tier Designation Process:

> Tier 1 students are those engaged in the core curriculum and meeting at-benchmark performance via summative screening and formative classroom data.
>
> Tier 2 designation occurs when students do not meet benchmark standards, are flagged via screeners or classroom formative data, and require additional small-group support beyond Tier 1. Instruction in Tier 2 is delivered by interventionists, instructional coaches, or teachers trained in targeted interventions, using standard protocols and weekly progress monitoring.
>
> Tier 3 is for students who demonstrate low response or continued risk after Tier 2 support; instruction becomes more individualized, often delivered by specialists, with higher frequency, smaller group size (or one-to-one), and daily progress monitoring.

By aligning data collection and analysis across these levels, MTSS systems maintained a continuous improvement loop: summative data refined curriculum and Tier 1 instruction; formative data guided targeted interventions and tier movement; and collaborative data teams ensured fidelity, monitored equity, and iterated system design. In cyber environments, digital dashboards, analytics, and student management systems strengthen visibility and accountability when used consistently.

Collaborative Problem Solving

MTSS depended on collaboration among general and special educators, administrators, counselors, and families. Critically, it also relied on teams of teachers who taught the same content (e.g., grade-level or departmental teams), as these professional learning communities analyzed common assessments, aligned instructional practices, and made collective decisions about which students required Tier 1 differentiation or Tier 2 support, promoting coherence and equity across classrooms. Regular meetings, shared protocols, and transparent communication promoted cohesive action plans and shared responsibility for student success (Choi et al., 2019). Together, these components provided a structure for equitable intervention delivery while maintaining flexibility to adapt across settings, including online learning environments.

Benefits of MTSS

A substantial body of research demonstrated that MTSS was an effective, equitable, and sustainable framework for improving academic, behavioral, and social-emotional outcomes for students when implemented with fidelity. MTSS was particularly effective because it integrated prevention, early intervention, and systematic data use, elements repeatedly shown to reduce learning gaps and improve schoolwide functioning (Freeman-Green et al., 2021; Fuchs & Fuchs, 2006). By organizing supports into tiers and ensuring that decisions were based on consistent data sources, MTSS provided a coherent structure for schools to proactively address student needs rather than relying on reactive or fragmented supports.

Academic Benefits

One of the most documented benefits of MTSS was its positive impact on academic achievement. Research showed that systematic tiered intervention produced significant growth in reading and mathematics for students across grade levels. For example, in a large-scale case study of elementary schools implementing RTI/MTSS, students receiving Tier 2 reading interventions demonstrated significantly greater gains in decoding and fluency compared to peers in non-MTSS schools (Al Otaiba et al., 2014).

Similarly, in a Florida multi-district study, schools implementing MTSS with high fidelity experienced double the rate of reading proficiency growth on state assessments compared to schools without MTSS structures (Balu et al., 2015). These improvements were not limited to students in intervention tiers; whole-school gains were observed due to stronger Tier 1 core instruction, improved alignment across grade-level teams, and more intentional data-based instructional practices.

MTSS also reduced special education misidentification by ensuring that students received evidence-based support before referral. Case studies in Minnesota and Colorado found that MTSS implementation decreased unnecessary special education placements by 30-60% while ensuring that students with genuine disabilities were identified more accurately and earlier (Hoover et al., 2020). This shift reflected the preventive intent of MTSS: early, targeted intervention reduced long-term academic struggles and prevented students from “falling through the cracks.”

Behavioral Benefits

On the behavioral side, MTSS, most notably through its behavioral framework of Positive Behavioral Interventions and Supports (PBIS), had a strong and well-established research base demonstrating effectiveness in improving student behavior and school climate. PBIS functioned as the behavioral arm of MTSS, applying the same tiered, data-based principles used in academic intervention to behavior and social-emotional development. In a large, multi-year randomized controlled trial examining PBIS implementation across more than 600 elementary and middle schools, Bradshaw et al. (2010) found that schools implementing PBIS with fidelity experienced approximately 33% reductions in office discipline referrals, significant decreases in suspensions, and measurable improvements in student-teacher relationships and perceptions of school safety. These outcomes reflected not only behavioral change but also broader improvements in school climate and relational trust.

Additional studies reinforced these findings at scale. Horner et al. (2009) reported that schools implementing PBIS with fidelity demonstrated sustained reductions in exclusionary discipline practices and greater consistency in behavioral expectations across classrooms. Similarly, McIntosh et al. (2014) found that PBIS implementation was associated with decreased disproportionate discipline outcomes for students of color, suggesting that data-based behavioral systems could function as equity-promoting structures when implemented intentionally.

Together, these studies highlighted the role of behavioral MTSS frameworks in reducing reactive disciplinary practices and replacing them with proactive, instructional approaches to behavior.

Behavioral MTSS also played a critical role in supporting social-emotional learning (SEL), particularly when SEL instruction was embedded within Tier 1 universal supports and reinforced through Tier 2 and Tier 3 interventions. Schools implementing PBIS consistently demonstrated improvements in student self-regulation, engagement, and sense of belonging, protective factors strongly associated with long-term academic and behavioral success (Sugai & Horner, 2020). By establishing predictable routines, explicitly teaching behavioral expectations, and reinforcing positive behavior, PBIS created conditions that supported the development of social-emotional competencies such as self-management, relationship skills, and responsible decision-making.

Research examining the intersection of MTSS and SEL further supported this integration. Lane et al. (2007) found that tiered behavioral frameworks incorporating SEL instruction resulted in reductions in disruptive behavior and improvements in academic engagement for students receiving Tier 2 supports. More recently, Cook et al. (2015) reported that schools integrating SEL within an MTSS framework experienced improvements in both behavioral outcomes and classroom instructional time, suggesting that SEL-enhanced MTSS models contributed to more effective learning environments overall. These findings underscored that SEL was not an “add-on” to MTSS, but rather a complementary component that strengthened behavioral and academic systems alike.

Collectively, this body of research indicated that MTSS implementation, through PBIS and integrated SEL practices, produced meaningful behavioral and climate-related benefits at both the student and school levels. When behavioral supports were delivered within a tiered, data-driven framework, schools were better positioned to promote positive behavior, reduce exclusionary discipline, and foster environments where students felt safe, supported, and connected. These outcomes further reinforced the role of MTSS as a comprehensive framework for addressing the full range of student needs beyond academics alone.

Whole-Child and Equity Benefits

MTSS was explicitly designed to support the whole child, ensuring that academic, behavioral, and social-emotional needs were not addressed in isolation. Research showed that MTSS implementation reduced outcome disparities for multilingual learners, students with disabilities, and economically disadvantaged students by providing access to tiered supports grounded in early identification and culturally responsive practices (Freeman-Green et al., 2021). For example, a case study in Oregon found that MTSS implementation decreased achievement gaps between White students and students of color by more than 25% in reading within three years (Everett et al., 2019). These gains were attributed to consistent progress monitoring, differentiated Tier 1 instruction, and culturally relevant Tier 2 interventions.

System-Level Benefits

At the systems level, MTSS strengthens collaboration, improves instructional alignment, and enhances organizational efficiency. Schools using MTSS typically implement grade-level or departmental data teams, which analyze common assessments, monitor intervention effectiveness, and make shared decisions about support. Research shows that these collaborative structures significantly improve teacher efficacy and reduce variability in instructional quality across classrooms (Donohoo, 2017). MTSS also creates a predictable data cycle, screen, intervene, monitor, adjust, that helps administrators allocate resources based on real-time needs and ensure consistent implementation.

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Why MTSS Works

MTSS was effective because it integrated several interdependent, research-supported principles that collectively strengthened instructional systems and improved student outcomes. First, MTSS emphasized prevention rather than reaction by prioritizing strong Tier 1 instruction and early identification of learning needs through universal screening, reducing reliance on a wait-to-fail model that delayed support for struggling students. Second, the framework was grounded in data-based decision making rather than intuition, requiring educators to use multiple sources of student data-screening, progress monitoring, and outcome measures-to guide instructional planning, intervention selection, and movement between tiers. This reliance on systematic data increased accuracy, consistency, and equity in instructional decisions (Burns & Gibbons, 2012; Gersten et al., 2009).

In addition, MTSS relied on collaborative teams rather than isolated teachers, recognizing that complex student needs were best addressed through shared problem-solving and collective expertise. Grade-level teams, intervention teams, and MTSS leadership teams regularly analyzed data, monitored intervention fidelity, and made instructional adjustments, which improved coherence and reduced variability in implementation (Batsche et al., 2014). The framework also prioritized evidence-based instruction over ad hoc interventions, requiring that both core instruction and targeted supports were grounded in practices with demonstrated effectiveness. This emphasis on instructional fidelity and alignment ensured that students received interventions likely to produce meaningful gains (Fixsen et al., 2005).

Finally, MTSS replaced one-size-fits-all approaches with tiered supports that increased in intensity based on student need, allowing instruction to be responsive, flexible, and scalable. Research consistently demonstrated that when these components-prevention, data use, collaboration, evidence-based instruction, and tiered support-were implemented with fidelity, schools experienced improved academic and behavioral outcomes at both the individual and system levels (Al Otaiba et al., 2019; Balu et al., 2015). Together, this integrated design made MTSS one of the most empirically supported and widely endorsed instructional frameworks in contemporary K-12 education.

Challenges and Barriers in Implementation

Despite its promise, many schools faced significant barriers to implementing MTSS with fidelity. Research consistently identified challenges related to resources, training, data systems, and long-term sustainability, particularly as schools scaled MTSS across grade levels and student populations (Freeman-Green et al., 2021; McIntosh & Goodman, 2016).

Resource Constraints

A recurring barrier in MTSS implementation was the limitation of personnel, time, and funding. Schools often lacked sufficient interventionists, coaches, or specialists to deliver Tier 2 and Tier 3 supports with the frequency and intensity required, which resulted in incomplete or uneven implementation across tiers. Scheduling constraints also made it difficult to build protected intervention blocks (e.g., WIN time) into the master schedule, especially at the secondary level where credit-bearing courses dominated student timetables. McIntosh and Goodman (2016) noted that schools attempting to implement MTSS without aligning schedules, staffing, and planning time frequently experienced “initiative fatigue,” in which teachers felt overextended and supports were layered on top of, rather than integrated within, existing practices. These resource constraints were compounded in rural and high-need districts, where staffing shortages and competing mandates limited the capacity to sustain robust MTSS structures (Burns et al., 2020).

Training and Professional Development

Effective MTSS implementation required that educators understood how to interpret data, select evidence-based interventions, deliver instruction across tiers, and apply behavioral support strategies. However, many teachers and school leaders reported limited preparation in these areas. Newell et al. (2021) found that insufficient professional development in data-based decision-making and intervention design was one of the most cited barriers to MTSS fidelity. Similarly, Freeman-Green et al. (2021) highlighted that when teachers were not explicitly trained to integrate culturally responsive practices within MTSS, inequities in referrals and supports could persist. Ongoing coaching, collaborative data meetings, and targeted training in both academic and behavioral interventions were essential; without them, MTSS risked becoming a procedural checklist rather than a robust instructional framework.

Data Integration and Infrastructure

MTSS depended on timely, accurate data across academic, behavioral, and social-emotional domains. In practice, however, schools often struggled with fragmented data systems. Academic data might reside in one platform, behavior incidents in another, and SEL screeners in a third. Managing and synthesizing these multiple data sources was time-consuming and technically challenging, particularly for schools without dedicated data support personnel (McIntosh & Goodman, 2016).

These integration issues were amplified in virtual and hybrid learning environments, where engagement metrics (e.g., log-ins, assignment completion, time-on-task) also became critical indicators. Evans et al. (2022) found that many online programs lacked unified dashboards that brought together academic performance, attendance, and behavioral indicators, which made it difficult for MTSS teams to form a complete picture of student needs or intervention effects. As a result, tier placement and monitoring decisions were often delayed or based on incomplete information.

Consistency, Fidelity, and Sustainability

Even when MTSS was initially implemented with enthusiasm, maintaining consistency and fidelity over time posed another major challenge. Without clear leadership structures, ongoing coaching, and systemwide communication, MTSS efforts often lost momentum or became compliance-driven, focusing more on completing forms than on improving instruction (McIntosh & Goodman, 2016). Turnover in leadership or key MTSS champions exacerbated this problem; new initiatives emerged, and MTSS was sometimes deprioritized or fragmented. Research also indicated that fidelity tended to be higher at Tier 1 than at Tiers 2 and 3, where interventions were more intensive and complex to coordinate (Burns et al., 2020). Freeman-Green et al. (2021) further noted that sustainability was closely tied to equity; when MTSS was not maintained as a continuous improvement framework, historically marginalized students might once again experience inconsistent access to support. Long-term success, therefore, depended on embedding MTSS into district policies, leadership practices, and professional learning systems rather than treating it as a short-term initiative.

In online programs, these challenges were amplified by reduced opportunities for real-time observation and the need to translate traditional face-to-face practices into digital formats. According to Guest et al. (2024), nearly half of virtual teachers reported difficulty determining when students were disengaged or experiencing academic challenges, and this lack of immediate feedback made it harder to initiate the early, preventative supports MTSS required. Addressing these barriers required intentional design and collaboration across all levels of the system.

Culturally Sustaining Practices

Culturally Sustaining Practices (CSP) provided a critical equity-focused lens within MTSS, ensuring that academic and behavioral supports honored, sustained, and elevated the cultural identities, languages, and community knowledge of all students. Rooted in the foundational work of Paris and Alim (2017), CSP moved beyond traditional approaches to cultural responsiveness by asserting that students' cultural ways of being were not simply assets to acknowledge; rather, they were resources that needed to be continually supported and expanded within instructional and intervention frameworks. As schools and cyber programs worked to address diverse learner needs, CSP offered a powerful complement to MTSS by promoting identity-affirming instruction, preventing biased referral patterns, and strengthening engagement across cultural contexts.

Culturally Sustaining Practices within MTSS

Equity was a central tenet of MTSS, yet many implementations focused primarily on data and logistics rather than cultural responsiveness. Integrating Culturally Sustaining Practices (CSP) ensured that interventions honored students' identities, languages, and communities (Paris & Alim, 2017). CSP within MTSS took several forms.

Designing Interventions That Are Linguistically and Culturally Relevant

One of the core applications of CSP within MTSS involved designing instructional and intervention practices that affirmed students' cultural and linguistic identities. Paris and Alim (2017) emphasized that CSP moved beyond mere cultural responsiveness by sustaining students' home languages, communication patterns, and cultural knowledge as essential components of instruction. Within an MTSS framework, this meant that Tier 1 curriculum materials, examples, texts, and problem-solving tasks reflected students' cultural backgrounds, while Tier 2 and Tier 3 interventions adapted instructional language and examples so they were accessible and meaningful for multilingual learners and culturally diverse students.

Research showed that when interventions integrated culturally relevant materials, such as bilingual texts, community-based examples, or culturally familiar narrative structures, students demonstrated higher engagement and improved reading and math outcomes (Aronson & Laughter, 2016; Gay, 2018). For instance, Freeman-Green et al. (2021) found that MTSS interventions incorporating culturally sustaining language scaffolds resulted in stronger Tier 2 responsiveness among multilingual learners. These adaptations ensured that interventions did not unintentionally alienate students who might already be marginalized within traditional academic systems.

Including Family and Community Voices in Data Discussions and Intervention Planning

CSP emphasized that families and communities were essential partners in the educational process rather than peripheral stakeholders. Within MTSS, this principle translated into involving families in goal setting, intervention selection, progress monitoring discussions, and data-based decision making. Research consistently showed that meaningful family engagement improved academic achievement, attendance, and behavior outcomes, particularly for students from historically marginalized groups (Jeynes, 2018). From a CSP perspective, this meant schools created space for families to share cultural knowledge, communication norms, and contextual insights that might shape how students learned or responded to interventions. Castro-Olivo (2014) found that culturally attuned collaboration with families led to improved SEL outcomes for Latinx students receiving Tier 2 supports. MTSS teams that incorporated family voice also reduced cultural misunderstandings in behavior referrals, improved intervention match, and fostered greater trust between schools and communities (Henderson & Mapp, 2002).

In cyber settings, incorporating family voice included virtual data conferences, multilingual communication tools, and opportunities for caregivers to shape intervention plans based on cultural norms at home.

Implicit bias training was essential in MTSS because Tier 2 and Tier 3 referral patterns were often influenced by teachers' perceptions, which might unintentionally reflect cultural bias. Research repeatedly documented disparities in referrals for behavior supports, special education, and discipline-particularly for Black, Latinx, Indigenous, and multilingual learners (Skiba et al., 2011). Culturally sustaining MTSS required educators to examine discipline data by subgroup, analyze disproportionality, and adapt behavioral expectations to reflect varied cultural norms for communication, emotional expression, and social interaction. Gregory et al. (2016) found that schools implementing culturally responsive behavioral supports experienced reductions in exclusionary discipline and improvements in teacher-student relationships.

Professional development that helped educators identify implicit bias, use strength-based language, and interpret behavior within cultural context contributed to more accurate Tier 2 identification and equitable access to supports (McIntosh & Goodman, 2016). When educators were trained to recognize cultural variability in classroom behavior, MTSS became a more equitable framework, reducing the over-referral of students of color to intensive support.

Embedding Social Emotional Learning

CSP within MTSS also included embedding social-emotional learning (SEL) curricula that reflected students' cultural identities, lived experiences, and community values. Traditional SEL programs often relied on norms rooted in dominant cultural perspectives, which could feel misaligned for students from diverse backgrounds (Jagers et al., 2019). Culturally sustaining SEL created explicit space for multiple ways of expressing emotions, communicating, resolving conflict, and building community. For example, Jagers, Rivas-Drake, and Borowski (2018) argued that SEL needed to incorporate sociopolitical awareness, cultural identity development, and critical consciousness to truly support students emotionally and behaviorally. Schools that embedded CSP within SEL-such as using storytelling from students' cultures, community-based mentors, or restorative practices rooted in cultural traditions-demonstrated stronger SEL outcomes, reduced behavior incidents, and increased student engagement (Romero et al., 2019). Within MTSS, culturally sustaining SEL strengthened Tier 1 behavioral expectations, improved the accuracy of Tier 2 referrals, and provided culturally attuned strategies for Tier 3 emotional or behavioral supports.

Freeman-Green et al. (2021) found that MTSS frameworks that explicitly integrated CSP showed improved engagement and decreased discipline disparities. Freeman-Green et al. (2021) conducted a systematic review examining how culturally responsive and culturally sustaining practices were embedded within MTSS across academic, behavioral, and social-emotional domains. Their analysis included 36 empirical and conceptual studies in which MTSS frameworks integrated CSP-related elements such as culturally relevant instruction, family engagement, identity-affirming behavioral supports, and data-based decision making that explicitly considered cultural context. The review found that MTSS frameworks integrating CSP typically included several shared practices:

Culturally Sustaining Tier 1 Instruction

Schools implementing CSP-infused MTSS modified Tier 1 instruction to ensure that curriculum materials, examples, and discourse patterns reflected students' cultural backgrounds.

Teachers incorporated community stories, home languages, and culturally meaningful contexts into core instruction. Freeman-Green et al. found that when Tier 1 became more culturally sustaining, fewer students-particularly multilingual learners and students of color-were inappropriately referred to Tier 2 or Tier 3 supports.

Equity-Oriented Tier 2 and Tier 3 Decision-Making

The study highlighted how MTSS teams that used CSP principles did not rely solely on universal screening scores for Tier 2 decisions. Instead, they contextualized data using students' cultural and linguistic backgrounds, ensuring that differences in dialect, language acquisition, or cultural communication norms were not misinterpreted as deficits. This approach reduced biased referrals to intensive interventions and special education.

Integration of Family and Community Knowledge

CSP-oriented MTSS systems incorporated structured opportunities for families to contribute cultural insight during team meetings, intervention planning, and progress monitoring conversations. Freeman-Green et al. reported that when schools systematically included caregiver voice in MTSS processes, intervention match improved, and student engagement in both academic and behavioral supports increased.

Behavior Supports Rooted in Cultural Context

In schools where PBIS was adapted using CSP principles, behavioral expectations were co-created with students and families, acknowledging cultural differences in communication, interaction, and community norms. Teachers were trained to interpret behaviors through a cultural lens, reducing misinterpretations that often led to disproportionate discipline. Freeman-Green et al. found that these CSP-informed PBIS models significantly decreased discipline disparities, particularly for Black and Latinx students.

Professional Development on Bias, Identity, and Culture

A key finding from Freeman-Green et al. was that MTSS systems integrating CSP provided ongoing professional development focused on implicit bias, cultural identity development, and asset-based views of student behavior. These trainings helped teachers distinguish between cultural differences and actual behavioral concerns, leading to more accurate Tier 2 behavioral referrals. Freeman-Green et al. (2021) found that MTSS frameworks explicitly integrating culturally sustaining practices, such as culturally aligned Tier 1 instruction, equity-focused referral processes, family-centered decision making, and culturally grounded behavioral supports, demonstrated improved academic engagement, stronger intervention responsiveness, and decreased discipline disparities.

For cyber schools, where students learned from varied geographic and cultural backgrounds, maintaining culturally sustaining approaches was essential for fostering connection and belonging. Virtual spaces could also be leveraged creatively through multilingual resources, culturally responsive content, and flexible communication methods to ensure inclusion and equitable access to support.

MTSS in Cyber and Hybrid Schools

The literature on MTSS in online education was emerging but remained limited. Existing studies highlighted persistent gaps and limited opportunities.

Implementation Trends

Research showed that virtual schools were adapting MTSS elements, such as tiered academic interventions and data dashboards, but often lacked full integration of behavioral and social-emotional components (Evans et al., 2022). Collaboration across remote staff remained inconsistent, and intervention tracking tools varied widely among programs.

Barriers

Online learning introduces both obstacles and advantages for MTSS. Barriers include inconsistent student attendance, communication delays, and limited visibility into nonacademic needs.

Resource Constraints

Resource constraints remained one of the most pervasive barriers to MTSS implementation across both traditional and virtual settings. In cyber environments, schools often faced limited personnel to provide Tier 2 and Tier 3 supports, restricted funding for intervention programs, and insufficient time built into virtual schedules for collaboration or intervention delivery. These issues directly undermined MTSS fidelity because Tier 2 and Tier 3 support required increased instructional intensity, frequent progress monitoring, and consistent intervention blocks that were often difficult to sustain without adequate staffing. Burns et al. (2020) found that rural, high-poverty, and virtual schools were significantly more likely to report shortages of interventionists, making it difficult to deliver timely supplemental instruction.

Inadequate Training and Professional Development

Effective MTSS implementation depended heavily on educators' ability to interpret data, design interventions, and integrate behavioral supports. However, many educators reported limited preparation in these areas, especially in virtual contexts where engagement metrics, SEL indicators, and attendance data also needed to be analyzed. Newell et al. (2021) identified inadequate professional development as one of the most significant impediments to MTSS fidelity, noting that teachers often lacked training in progress monitoring and culturally responsive intervention design. In virtual schools, this gap widened because teachers also had to learn how to deliver interventions through tele-instruction and interpret data from digital learning platforms.

Data Integration and Fragmented Information Systems

MTSS depended on efficient data collection, analysis, and interpretation across academic, behavioral, SEL, and attendance indicators. Virtual schools often used multiple platforms-LMS systems, behavior trackers, benchmark assessments, and communication logs-that were not integrated into a single dashboard. This fragmentation created delays in decision making and increased the risk of incomplete or inaccurate tier placements. McIntosh and Goodman (2016) found that schools with fragmented data systems exhibited lower MTSS fidelity because staff lacked a unified view of student needs. In virtual environments, Evans et al. (2022) noted that teachers struggled to triangulate engagement data, screeners, and communication records, complicating the identification of Tier 2 needs.

Inconsistent Engagement and Attendance

Student engagement was a core early-warning indicator in MTSS, but it was uniquely volatile in virtual settings. Students might fail to log in, leave sessions early, remain off-camera, or fail to submit work, making it difficult for teachers to gauge learning readiness or behavioral concerns. Guest et al. (2024) reported that nearly half of virtual teachers experienced difficulty identifying disengagement, which led to delays in Tier 2 interventions. Turnaround for Children (2020) similarly found that inconsistent engagement disrupted the MTSS data cycle because attendance and task-completion metrics were often the first indicators of academic risk online.

Limited Visibility into Non-Academic Needs

Unlike traditional environments where teachers observed students daily, virtual teachers had limited visibility into students' emotional well-being, home life, or environmental stressors. This lack of insight constrained Tier 1 SEL support and could lead to under-identification of students needing Tier 2 behavioral or emotional interventions. Evans et al. (2022) found that virtual teachers expressed lower confidence in recognizing signs of distress or behavioral escalation in online learning spaces. This gap increased the risk that students' nonacademic needs went unaddressed until they manifested as academic failure or disengagement.

Communication Delays Between Students, Families, and Teachers

MTSS relied on rapid, clear communication to coordinate supports, but virtual learning introduced delays due to asynchronous messaging, email backlogs, and inconsistent caregiver availability. Communication lags made it harder to deliver timely interventions, coordinate Tier 2 plans, and maintain fidelity. Chow et al. (2020) highlighted that communication breakdowns impeded progress monitoring because teachers could not promptly clarify misunderstandings or adjust instruction. This led to slower intervention cycles and missed opportunities for early support.

Consistency, Fidelity, and Sustainability Challenges

Even when MTSS was implemented effectively, maintaining fidelity over time remained challenging. Schools might lose momentum without leadership stability or continuous professional development. McIntosh and Goodman (2016) documented that fidelity was particularly difficult to maintain in Tier 2 and Tier 3, where interventions were more complex. Virtual schools faced additional challenges due to staff turnover, inconsistent professional development participation, and the need for constant adaptation of virtual materials.

Opportunities

However, digital platforms also provided unique opportunities for personalization and responsiveness that could strengthen MTSS implementation in virtual contexts. Automated alerts, progress dashboards, and predictive analytics enabled teachers to identify disengagement patterns earlier and intervene more efficiently. Many systems integrated embedded SEL modules and real-time engagement metrics, allowing educators to monitor academic, behavioral, and affective indicators simultaneously (Guest et al., 2024). These tools, when used with fidelity, supported timely Tier 1 and Tier 2 responses and increased the visibility of student needs in environments where traditional cues were less observable (Guest et al., 2024).

Cyber programs also needed to proactively address persistent inequities in technology access, internet connectivity, device reliability, and home learning conditions. Research continued to show that digital learning environments could unintentionally widen gaps for students from historically marginalized groups when these structural factors were not intentionally addressed (Borup et al., 2020; Rice et al., 2021). Integrating culturally sustaining practices (CSP) within virtual MTSS frameworks helped mitigate these disparities by centering students' lived experiences, linguistic backgrounds, and community identities. CSP-aligned MTSS systems promoted flexible pathways for instruction, honored multiple ways of demonstrating learning, and created relational practices that built belonging even when students were not physically present. When virtual MTSS intentionally incorporated CSP, it expanded opportunities for academic access and emotional support, particularly for students who might otherwise remain invisible in online settings. Embedding culturally sustaining practices within virtual MTSS helped mitigate these inequities by centering students' lived realities and promoting flexibility in instructional delivery.

Overall, the literature emphasized that MTSS could succeed in cyber schools when it was systematically adapted, data-rich, and collaboratively maintained rather than simply transplanted from brick-and-mortar models. Research showed that while tiered frameworks such as MTSS, RTI, and PBIS remained valuable in virtual environments, they required intentional restructuring to account for differences in communication, engagement, and progress monitoring (Institute of Education Sciences [IES], 2021). Studies of virtual Tier 2 and Tier 3 systems similarly noted that many core in-person MTSS components could be transferred online, but only when digital-specific tools, workflows, and supports were used to deliver interventions effectively (Hanover Research, 2020). Broader MTSS scholarship also reinforced that high-quality implementation-across physical or virtual settings-depended on ongoing collaboration, shared ownership, and systematic use of academic and behavioral data to guide decisions (Great Schools Partnership, 2023). Collectively, these sources underscored that virtual MTSS thrived not by replicating traditional methods but by adapting them to the affordances and constraints of online learning.

Summary

The literature revealed that while MTSS was a proven framework for improving academic and behavioral outcomes, its translation to cyber education remained incomplete. Implementation Science provided a pathway for fidelity and sustainability, while Culturally Sustaining Pedagogy ensured that MTSS remained equitable and inclusive. The intersection of these theories offered the foundation for this applied research study.

This chapter synthesized historical, theoretical, and practical perspectives on MTSS and identified key gaps, including the need for:

- Culturally responsive adaptations within virtual contexts
- Consistent data integration across online systems

- Structured collaboration for remote educators and families

Chapter Three outlined the methods used in this applied research study, including the design, participants, data collection procedures, and analysis plan for examining MTSS implementation in a K-12 cyber program.

Chapter 3

Methods Overview

This chapter outlined the quantitative design, setting, participants, instrumentation, data collection procedures, variables, and statistical analyses used to examine academic growth within the Multi-Tiered System of Supports (MTSS) framework in a K-12 cyber program. The study investigated student growth on the STAR Benchmark assessment from August to January and compared outcomes across two WIN (What I Need) intervention modalities: in-person WIN sessions and virtual WIN sessions delivered via Microsoft Teams. Ethical considerations, reliability, and validity were also addressed.

Research Design

This study employed a quantitative, quasi-experimental design with:

- A repeated measures component evaluating student growth between two time points (August vs. January STAR scores), and
- A comparative component analyzing differences between two naturally occurring groups (in-person WIN vs. virtual WIN).

A quasi-experimental design was appropriate because students were not randomly assigned to intervention groups; instead, they participated based on scheduling, family preference, transportation, or staffing availability. This design was common in applied educational settings where randomization was not feasible, but empirical evaluation was needed.

Two statistical procedures were used:

1. A paired-samples t-test measured significant growth from August to January for the entire sample.
2. An independent-samples t-test compared mean STAR growth between in-person WIN and virtual WIN students.

These quantitative techniques aligned directly with the research questions and allowed the researcher to determine whether MTSS structures and intervention modalities supported measurable academic improvement.

Research Questions

RQ1:

To what extent did students enrolled in the cyber program demonstrate academic growth on the STAR Benchmark assessment from August to January?

$H1_0$: There was no statistically significant difference in STAR scores from August to January.

$H1_a$: Students demonstrated significant growth in STAR scores from August to January.

RQ2:

Was there a statistically significant difference in STAR Benchmark growth between students receiving in-person WIN support and those receiving virtual WIN support?

$H2_0$: There was no difference in growth between in-person WIN and virtual WIN groups.

$H2_a$: Students who received in-person WIN support demonstrated greater growth than students who received virtual WIN support.

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Setting

The study took place in a large Pennsylvania-based K-12 cyber program within a public school district. The program served students across multiple partner districts and offered a blend of asynchronous coursework and synchronous support sessions. MTSS structures included universal screening, weekly WIN time, and targeted interventions aligned with academic needs. WIN was delivered in two modalities:

- In-person WIN: Small-group academic intervention at designated physical sites
- Virtual WIN: Intervention delivered synchronously via Microsoft Teams

The STAR Benchmark assessment was administered universally three times per year and served as the program's primary academic screening tool.

Participants

Population

The target population included approximately 50 K-6 students enrolled in the cyber program who completed both the August (fall) and January (winter) STAR Benchmark assessments.

Sample

A convenience sample was used consisting of students who:

- Completed both assessments, and
- Participated in WIN intervention (either in-person or virtual).

Students who did not participate in WIN or who had missing assessment data were excluded to ensure accurate measurement of growth and modality effects.

Group Definitions

In-person WIN group: Students who received face-to-face intervention

Virtual WIN group: Students who received intervention via Microsoft Teams

Final sample sizes were reported in the results chapter.

Instrumentation

STAR Benchmark Assessment

Renaissance STAR Reading and STAR Math were computer-adaptive assessments developed by Renaissance Learning and were widely used in K-12 settings for universal screening, progress monitoring, and growth measurement. The assessments adjusted item difficulty in real time based on student responses, allowing for precise measurement of achievement with fewer test items.

Both assessments were administered online through Renaissance's secure platform using district-approved devices. Students completed the assessments independently in both virtual and in-person settings, making STAR appropriate for cyber learning environments.

STAR Reading assessed English Language Arts skills, including reading comprehension and vocabulary. STAR Math assessed mathematical skills such as number operations, algebraic reasoning, geometry, and data analysis. The assessments measured reading and mathematics only and did not assess science or social studies content.

Although STAR assessments were not globally timed, each item had an embedded time limit to support test validity. Total administration time varied by student but typically ranged from 20 to 30 minutes. All items were multiple choices, and no constructed-response items were included.

Reliability and Validity

According to the Renaissance Technical Manuals, STAR assessments demonstrated strong psychometric properties:

- Internal consistency reliability: Cronbach's alpha ranged from .86 to .92

- Test-retest reliability: Approximately $r = .80$
- Validity: STAR demonstrated strong concurrent and predictive validity with state assessments

STAR assessments were appropriate for this study due to their vertically scaled scores, which allowed performance to be measured across grade levels and over time on a continuous developmental scale. This feature supported accurate growth analysis and aligned with MTSS progress monitoring practices (Renaissance, 2023).

STAR assessments were administered using standardized digital procedures across instructional settings. Renaissance specified that administration conditions, adaptive algorithms, and scoring procedures remained consistent regardless of student location, supporting score comparability across virtual and in-person contexts (Renaissance, 2023).

Additionally, STAR aligned with Pennsylvania Department of Education MTSS guidelines for universal screening, including reliability, validity, and efficiency requirements (PDE, 2023).

Variables

The independent variable for this study was WIN (What I Need) intervention modality, which represented the format through which targeted instructional supports were delivered to students within the MTSS framework. This variable was operationalized as a dichotomous indicator, distinguishing between virtual and in-person delivery models. Students assigned a value of 0 received WIN interventions delivered virtually through synchronous online platforms, such as Microsoft Teams, while students assigned a value of 1 participated in WIN interventions delivered in person within a physical school setting. This operational definition allowed for clear comparison between intervention modalities and supported quantitative analysis of differences in student growth outcomes associated with the mode of WIN intervention delivery.

Dependent Variable

STAR Growth Score

Calculated as:

January STAR Score - August STAR Score

Control Variables

Student growth for this study is calculated using the difference between assessment scores across two time points, specifically by subtracting the August STAR score from the January STAR score. This calculation provides a direct measure of academic growth over the designated instructional period and allows for comparison of student progress across intervention modalities. By focusing on change over time rather than absolute performance, this approach accounts for individual starting points and aligns with MTSS practices that emphasize growth monitoring and responsiveness to intervention.

Depending on data availability, several control variables may be included in the analysis to account for factors that could influence student outcomes independent of the WIN intervention modality. These covariates may include grade level, which helps control developmental and curricular differences across grades, and baseline performance level, which accounts for initial achievement prior to intervention. Attendance may also be included, as consistent participation in instructional and intervention activities can affect student growth. Additionally, demographic characteristics - such as multilingual learner (MLL) status and special education status-may be incorporated to control variability related to student support needs and to support more equitable interpretation of results. Including these variables, when accessible, strengthens the validity of the analysis by reducing potential confounding effects and providing a more accurate estimate of the relationship between WIN intervention modality and student growth.

If accessible, the following may be included as covariates:

- Grade level
- Baseline performance level
- Attendance
- Demographic characteristics

Data Collection

Universal benchmarking was a foundational component of this study and served as the primary mechanism for measuring student achievement and growth within the MTSS framework. All students included in the study completed the STAR universal benchmark assessment during two district-established assessment windows: once in August at the beginning of the school year and again in January at the conclusion of the fall instructional period. These benchmarking windows were consistent across both groups in the study-students participating in virtual WIN interventions and those participating in in-person WIN interventions-ensuring uniformity in timing, expectations, and assessment conditions.

The STAR assessments were administered digitally using standardized procedures established by the school district. Students assigned to the virtual WIN group completed the assessments remotely through secure online access, while students assigned to the in-person WIN group completed the assessments on district devices within a supervised school setting. Although the physical testing environments differed, the assessment itself remained identical across groups, including item pools, adaptive algorithms, timing, scoring procedures, and reporting metrics. All students received the same directions and completed the assessments independently, consistent with STAR administration guidelines. This standardized administration allowed for valid comparison of results across both instructional modalities.

Benchmark results were used by educators to inform WIN (What I Need) instructional planning and MTSS decision-making at all tiers. At Tier 1, STAR data were reviewed to evaluate the effectiveness of core instruction and to identify students who required additional support. At Tier 2, students identified through benchmark scores as needing targeted intervention were assigned to WIN supports based on skill gaps identified in STAR domain-level data. At Tier 3, students demonstrating significant academic risk received more intensive, individualized interventions, with STAR data serving as one of multiple data points used to guide instructional decisions. While the structure and goals of WIN remained consistent across both groups, the primary difference lay in the delivery modality: virtual WIN interventions were delivered synchronously through online platforms, while in-person WIN interventions occurred face-to-face within the school building. The content, focus on targeted skills, frequency of intervention, and progress monitoring expectations remained aligned across modalities to the greatest extent possible.

Data for this study were collected through district assessment systems following established data governance protocols. Only de-identified student data were extracted for research purposes, and no personally identifiable information was included in the dataset provided to the researcher. Each student was assigned a unique study identifier to allow for longitudinal analysis while preserving confidentiality. All data were stored on secure, password-protected district systems, and access was limited to authorized personnel. Data analysis focused on comparing growth outcomes between August and January using STAR scale scores, with analyses conducted at the group level rather than the individual level to further protect student privacy. Findings were reported only in aggregate form, ensuring that no individual student, teacher, or subgroup could be identified. Through these procedures, the study maintained strong ethical protections while leveraging universal benchmarking data to examine the effectiveness of WIN intervention modalities within a cyber MTSS framework.

WIN Assignment

Students identified as requiring targeted academic support through the universal benchmarking and MTSS review process were assigned to a WIN (What I Need) intervention group based on instructional need and program structure. Following analysis of August STAR benchmark data, educators and intervention teams reviewed student performance, including overall scale scores and domain-specific skill data, to determine eligibility for targeted supports beyond core instruction. Students meeting criteria for Tier 2 or Tier 3 intervention were then assigned to one of two WIN intervention modalities: in-person WIN or virtual WIN delivered via Microsoft Teams.

Assignment to WIN modality was determined by the student's instructional program of enrollment and access to in-person services rather than by student choice or academic performance alone. Students participating in the in-person model received targeted WIN instruction within the school building during designated WIN blocks, allowing for face-to-face interaction with instructional staff. Students participating in the virtual model received WIN instruction synchronously through Microsoft Teams, where interventionists provided live, small-group or individualized support using digital instructional resources. In both modalities, WIN sessions were scheduled consistently and focused on addressing specific skill deficits identified through STAR data and other supporting measures.

Although the mode of delivery differed, the purpose, structure, and expectations of WIN remained consistent across both groups. All students received targeted instruction aligned to their identified needs, followed similar intervention timelines, and were monitored using the same assessment tools and data review processes. This parallel structure ensured that differences in student outcomes could be examined in relation to intervention modality while maintaining consistency in instructional intent, intensity, and MTSS alignment.

Data Extraction

The researcher will extract anonymized STAR scores from the district's data warehouse.

Data Cleaning

a. Removing missing or incomplete cases
b. Ensuring matching August to January scores
c. Verifying correct group assignment
d. Checking for outliers

Computation of Growth Scores

Growth = January score minus August score for each student.

Statistical Analysis

Conducted using SPSS or Excel based data tools.

Data Extraction, Cleaning, and Analysis Procedures

This applied internal improvement study relied exclusively on existing academic performance data collected through routine instructional and assessment practices; no data were collected directly from students for research purposes. Students completed the STAR universal benchmark assessment during district-established windows in August and January as part of standard MTSS procedures. These assessments were administered digitally in both instructional models. Students assigned to the virtual WIN group completed the assessment remotely using secure district-approved platforms, while students assigned to the in-person WIN group completed the assessment on district devices in a supervised school setting. The assessment content, administration procedures, adaptive algorithms, and scoring processes were identical across both groups, ensuring comparability of results. Benchmark data were used instructionally to guide WIN placement, skill grouping, and intervention planning at all tiers, independent of the research study.

Following the completion of the January benchmarking window, the researcher extracted anonymized STAR assessment data from the district's secure data warehouse. Prior to researcher access, all personally identifiable information was removed by the district in accordance with data governance policies. The dataset included only variables necessary for analysis, such as assessment scores, testing windows, grade level, WIN modality assignment, and approved covariates when available. Each student was assigned a unique, non-identifiable study code to allow matching of August and January records while preserving confidentiality. Data were stored and accessed exclusively on password-protected district systems, and no data were downloaded to personal devices or shared externally.

Once extracted, the dataset underwent a systematic data cleaning process to ensure accuracy and integrity. This process included removing cases with missing or incomplete assessment records, verifying that each included student had a matched August and January STAR score, and confirming correct assignment to either the virtual or in-person WIN group based on district records. Additional checks were conducted to identify potential data entry errors or statistical outliers that could distort growth analyses. Decisions regarding data inclusion or exclusion were documented to maintain transparency and replicability.

Student growth was calculated using a consistent and clearly defined formula: January STAR scale score minus August STAR scale score for each student. This approach produced an individual growth score that reflected progress over the fall instructional period while accounting for baseline performance. Growth scores were then aggregated and analyzed at the group level to compare outcomes between students receiving virtual WIN interventions and those receiving in-person WIN interventions. Analyses incorporated control variables, when available, to account for grade-level differences, baseline achievement, attendance, or identified student support needs.

Statistical analyses were conducted using SPSS or Excel-based data analysis tools, depending on district access and analytical needs. Descriptive statistics were used to summarize group characteristics and growth patterns, and comparative analyses were conducted to examine differences in growth between WIN modalities. Throughout the analysis process, results were reported only in aggregate form. No individual student, educator, or subgroup was identified in any reports or findings.

This study was designed as an applied internal improvement effort using existing de-identified academic data; it presented minimal risk to participants. Student identities were protected through anonymization, secure data storage, and restricted access, and participation in the study had no impact on instructional decisions, grades, placement, or services. These procedures ensured ethical compliance with district data governance standards, FERPA requirements, and IRB expectations for confidentiality and data protection.

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Data Analysis

Analysis for RQ1: Student Growth

- A paired samples *t*-test was used to compare:
- Mean STAR score in August
- Mean STAR score in January
- This test determined whether the change in scores was statistically significant.

Analysis for RQ2: Modality Comparison

- An independent samples *t*-test was used to compare:
- Mean STAR growth for in-person WIN students
- Mean STAR growth for virtual WIN students

Assumptions

Both analyses were checked for:

- Normality
- Homogeneity of variance
- Independence of observations

If assumptions were violated, appropriate nonparametric tests or adjusted procedures (e.g., Welch's *t*-test) were used.

Ethical Considerations

This study relied exclusively on existing, de-identified student data and did not involve the collection of any new information from participants. At no point were student names, identification numbers, dates of birth, addresses, or any other personally identifiable information (PII) accessed, recorded, or analyzed. Prior to the researcher's access, all data were stripped of direct and indirect identifiers by the school district in accordance with established data governance protocols, ensuring that individual students could not be identified by the researcher either directly or through data triangulation.

All research data were stored and accessed solely within secure, password-protected district systems that met institutional data security requirements. Access to these systems was limited to authorized personnel, and the researcher adhered to district policies regarding data handling, storage, and confidentiality. No data was downloaded to personal devices, shared externally, or stored on non-district platforms. Data were used only for the purposes outlined in this study and were not retained beyond the approved research timeline.

Research procedures complied fully with the school district's data governance policies as well as the requirements of the Family Educational Rights and Privacy Act (FERPA). The use of archival, de-identified data ensured that student privacy was protected and that no individual student could be singled out or adversely affected as a result of participation in the study. Additionally, participation in this research was entirely independent of instructional decision-making. The data analyzed were not used to inform grading, placement, intervention eligibility, or any educational services, and findings were reported only in aggregate form. As a result, the study posed no risk to students, preserved confidentiality, and maintained clear ethical separation between research activities and instructional practices.

Approval from the Institutional Review Board (IRB) was obtained prior to analysis.

Trustworthiness, Reliability, and Validity of the Study

Although quantitative research did not use qualitative criteria such as "credibility" or "trustworthiness," the following quantitative validity principles applied:

Reliability

The assessment data used in this study demonstrated strong reliability based on established psychometric evidence from the STAR assessment technical documentation. According to the STAR Reading and STAR Math Technical Manuals published by Renaissance, the assessments exhibited high internal consistency and test-retest reliability across grade levels, with reported reliability coefficients generally meeting or exceeding accepted thresholds for educational decision-making (Renaissance, 2023). These reliability metrics indicated that STAR assessments produced stable and consistent results over time when measuring student achievement and growth. In addition, all data extraction procedures for this study followed standardized, district-documented protocols. Data were pulled using consistent parameters across time points, ensuring uniformity in reporting windows, student inclusion criteria, and variable definitions. This standardization further strengthened the reliability of the dataset and reduced the likelihood of procedural error influencing results.

Internal Validity

Several common threats to internal validity, such as history, maturation, and selection bias, were minimized through the design of this study. The same standardized assessment tool (STAR) was used consistently across all measurement points, reducing instrumentation threats and ensuring comparability of scores over time. Although the comparison groups were naturally occurring rather than randomly assigned, they were comparable in purpose, as all students were enrolled in the same cyber program and participated in the same overarching MTSS framework. Additionally, growth calculations accounted for baseline differences by examining student progress relative to their initial performance levels rather than relying solely on raw scores. This approach strengthened causal inferences by focusing on growth trajectories and reduced the influence of preexisting achievement differences between groups.

External Validity

The generalizability of the findings was intentionally bounded. Results were most applicable to cyber students participating in similar virtual MTSS structures, particularly those using adaptive online curricula and operating within virtual programs that included WIN (What I Need) periods or structured intervention blocks. While these parameters limited broad generalization to all educational settings, the findings remained relevant to a growing number of cyber, hybrid, and blended learning programs that were expanding nationally. As virtual education models continued to scale and refine MTSS implementation, the results of this study offered practical insights that informed decision-making and program design in comparable contexts.

Summary

This chapter described the quantitative methodology used to examine academic growth and the impact of WIN intervention modality within a K-12 cyber MTSS framework. Using STAR Benchmark data, the study evaluated both within-group growth from August to January and between-group differences between in-person and virtual WIN interventions. The selected design, instruments, variables, procedures, statistical analyses, and ethical safeguards aligned with the study's purpose of improving equitable MTSS implementation in cyber education.

Chapter 4

Results

Introduction

The purpose of this applied research study was to examine academic growth among students enrolled in a K-12 cyber program implementing a Multi-Tiered System of Supports (MTSS) framework. All participants in the study were cyber students; however, they received intervention support through two different delivery modalities. Some students attended in-person WIN (What I Need) intervention sessions at the program's drop-in center, while others participated in virtual WIN sessions delivered through Microsoft Teams. The study compared the effectiveness of these two intervention delivery formats. Academic growth was measured using the Renaissance STAR Benchmark assessment administered at two time points during the academic year (August and January).

The study addressed the following research questions:

RQ1: To what extent did students enrolled in the cyber program demonstrate academic growth on the STAR Benchmark assessment from August to January?

RQ2: Was there a statistically significant difference in STAR Benchmark growth between students receiving in-person WIN support and those receiving virtual WIN support?

To answer the research questions, two statistical procedures were used. First, a paired samples t-test was conducted to examine overall academic growth across the entire sample of cyber students by comparing STAR Benchmark scores from the August administration (pretest) to the January administration (posttest). This analysis determined whether students enrolled in the cyber program demonstrated statistically significant academic growth over the course of the semester, regardless of intervention delivery format.

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Second, an independent samples t-test was conducted to compare mean growth scores between the two intervention groups: cyber students who attended in-person WIN (What I Need) sessions at the drop-in center and cyber students who participated in virtual WIN sessions delivered through Microsoft Teams. This analysis examined whether differences in academic growth were associated with the intervention delivery modality.

This chapter presents the results of the statistical analysis. First, the dataset and sample characteristics are described. Next, descriptive statistics for STAR scores and growth outcomes are reported. Finally, results are presented by research question.

Description of the Dataset

The dataset consisted of student STAR Benchmark assessment records collected from the cyber program during the fall semester. Student scores from the August universal screening window and the January benchmark window were extracted and paired to measure academic growth over time.

After removing incomplete records and students without both benchmark scores, the final dataset included N = 28 student records. Students represented multiple grade levels within the cyber program, including grades Kindergarten to 6th. Students were categorized into two naturally occurring intervention groups based on their participation in weekly WIN sessions:

In-Person WIN: Students attending regularly scheduled WIN (What I Need) intervention sessions at the district's Drop-In Center during the school week. These sessions occurred weekly on Wednesdays and provided students with direct, in-person academic support aligned to identified learning needs Virtual WIN: Students receiving regularly scheduled WIN intervention support remotely through Microsoft Teams. These sessions also occurred weekly on Wednesdays and provided targeted academic support in a virtual format aligned to students' identified learning needs.

Group placement was determined by scheduling availability, family preference, transportation access, and program logistics rather than random assignment.

Table 1

Sample Reading Characteristics

Characteristic	n	Percentage
In-Person WIN	16	57.1%
Virtual WIN	12	42.9%
Total Students	28	100%
Grade K-2	11	39.3%
Grade 3-4	7	25.0%
Grade 5-6	10	35.7%

The final dataset included 28 students with matched fall and winter STAR Reading scores. Of these students, 16 (57.1%) participated in in-person WIN sessions, while 12 (42.9%) participated in virtual WIN sessions. Students represented grades K through 6, with 39.3% in grades K-2, 25.0% in grades 3-4, and 35.7% in grades 5-6. No students in grades 7 or 8 were included in the dataset.

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Table 2

Sample Math Characteristics

Characteristic	n	Percentage
In-Person WIN	15	57.7%
Virtual WIN	11	42.3%
Total Students	26	100%
Grade K-2	10	38.5%
Grade 3-4	6	23.1%
Grade 5-6	10	38.5%

The final math dataset included 26 students with matched fall and winter STAR Math scores. Of these students, 15 (57.7%) participated in in-person WIN sessions, while 11 (42.3%) participated in virtual WIN sessions. Students represented grades K through 6, with 38.5% in grades K-2, 23.1% in grades 3-4, and 38.5% in grades 5-6.

Descriptive Statistics

Descriptive statistics were calculated for August STAR scores, January STAR scores, and overall growth scores. Growth scores were calculated by subtracting the average August benchmark score from the average January benchmark score for the whole group. Overall, students demonstrated measurable growth between the two testing windows. Table 2 provides descriptive statistics for STAR scores across both benchmark administrations.

Descriptive statistics indicated that the mean August STAR Reading score was 1012.7 (SD = 118.6), while the mean January STAR score increased to 1056.9 (SD = 113.2). Students demonstrated an average growth of 44.2 points across the assessment period, with growth scores ranging from -2 to 238.

Table 3

Descriptive Statistics for Reading STAR Benchmark Scores

Measure	Mean	Standard Deviation	Minimum	Maximum
August Reading STAR Score	1012.7	118.6	615	1150
January Reading STAR Score	1056.9	113.2	853	1178
Growth Score	44.2	56.9	-2	238

Table 4

Descriptive Statistics for Math STAR Benchmark Scores

Measure	Mean	Standard Deviation	Minimum	Maximum
August Math STAR Score	1001.4	114.8	801	1155
January Math STAR Score	1019.7	118.2	887	1164
Growth Score	18.3	42.6	-55	111

Descriptive statistics were also calculated separately for each intervention group to compare baseline performance and growth patterns between students participating in in-person and virtual WIN sessions.

Table 5

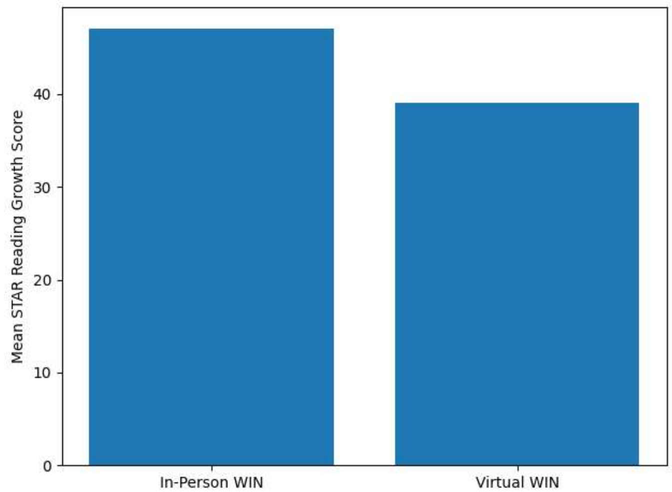
Descriptive Statistics by Intervention Group – Reading

Group	August Mean	January Mean	Growth Mean	SD Growth
In-Person WIN	1008.9	1056.5	47.6	39.5
Virtual WIN	1017.8	1057.1	39.3	42.8

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Figure B1

In-Person vs. Online Reading Growth Comparison



Note. Mean STAR Reading growth scores from August to January are displayed for cyber students receiving in-person WIN interventions at the Drop-In Center and students receiving virtual WIN interventions through Microsoft Teams. While students attending in-person WIN sessions demonstrated slightly higher average growth than those participating in virtual WIN sessions, the difference between groups was not statistically significant based on the independent samples *t*-test.

Table 6

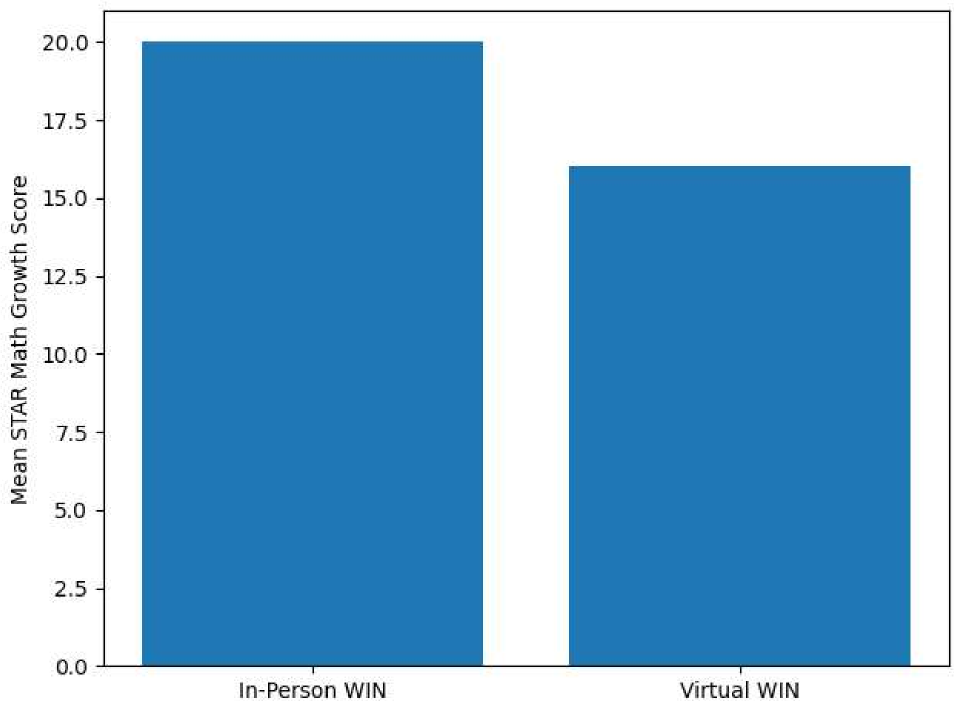
Descriptive Statistics by Intervention Group – Math

Group	August Mean	January Mean	Growth Mean	SD Growth
In-Person WIN	999.5	1018.2	18.7	39.4
Virtual WIN	1004.1	1021.6	17.5	46.5

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Figure B2

In-Person vs. Online Math Growth Comparison



Note. Comparison of mean STAR Math growth between students receiving in-person WIN support and those receiving virtual WIN support. Students participating in in-person WIN demonstrated slightly higher mean growth (M = 18.7) compared to students receiving virtual WIN support (M = 17.5), though the difference was not statistically significant.

Descriptive statistics were also calculated separately for each intervention group to compare baseline performance and growth patterns between students participating in in-person and virtual WIN sessions. As shown in Table 6, students receiving in-person WIN support demonstrated a mean growth of 18.7 points, while students receiving virtual WIN support demonstrated a mean growth of 17.5 points between the August and January benchmark assessments.

Results by Research Question

Research Question 1

RQ1: To what extent did students enrolled in the cyber program demonstrate academic growth on the STAR Benchmark assessment from August to January?

To examine overall academic growth, paired samples t-tests were conducted comparing August and January STAR Benchmark scores for both Reading and Math.

Reading Growth

A paired samples t-test was conducted to examine changes in STAR Reading scores for the entire sample of students enrolled in the cyber program who participated in the study. This analysis compared students' STAR Reading benchmark scores from the August administration (pretest) to their scores from the January administration (posttest) in order to determine whether overall academic growth occurred across the assessment period.

Results indicated a statistically significant increase in student scores, $t(27) = 4.12$, $p < .001$, suggesting that the full sample of cyber students demonstrated measurable academic growth between the two benchmark administrations. On average, students experienced an increase of 44.2 points in STAR Reading scores across the assessment period. These findings indicate that, when considered as a whole group, students participating in the cyber program demonstrated positive academic progress during the first semester of the academic year.

Table 7

Paired Samples t-Test Results for STAR Reading Growth

Variable	Mean Difference	SD	t	df	p
August vs January	+44.2	56.9	4.12	27	<.001

Math Growth

A paired samples t-test was conducted to examine changes in STAR Math scores for the entire sample of students enrolled in the cyber program who participated in the study. This analysis compared students' STAR Math benchmark scores from the August administration (pretest) to their scores from the January administration (posttest) to determine whether overall academic growth occurred across the assessment period.

Results indicated a statistically significant increase in student scores, $t(25) = 2.19$, $p = .038$, suggesting that the full sample of cyber students demonstrated measurable academic growth in mathematics between the two benchmark administrations. On average, students experienced an increase of 18.3 points in STAR Math scores across the assessment period. These findings indicate that, when considered as a whole group, students participating in the cyber program demonstrated positive academic progress in mathematics during the first semester of the academic year.

Table 8

Paired Samples t-Test Results for STAR Math Growth

Variable	Mean Difference	SD	t	df	p
August vs January	+18.3	42.6	2.19	25	.038

A paired samples t-test was conducted to examine differences between August and January STAR Math scores. Results indicated that students demonstrated statistically significant growth across the benchmark period, $t(25) = 2.19$, $p = .038$, with an average increase of 18.3 points.

Research Question 2

RQ2: Was there a statistically significant difference in STAR Benchmark growth between students receiving in-person WIN support and those receiving virtual WIN support?

Independent samples *t*-tests were conducted to compare growth outcomes between students receiving in-person WIN support and those receiving virtual WIN support for both Reading and Math benchmark assessments.

Reading Results

Students receiving in-person WIN support demonstrated a mean growth score of 47.6 STAR points (SD = 39.5), while students receiving virtual WIN support demonstrated a mean growth score of 39.3 STAR points (SD = 42.8). An independent samples t-test indicated that the difference in growth between the two groups was not statistically significant, $t(26) = 0.56$, $p = .58$.

Math Results

Students receiving in-person WIN support demonstrated a mean growth score of 18.7 STAR points (SD = 39.4), while students receiving virtual WIN support demonstrated a mean growth score of 17.5 STAR points (SD = 46.5). An independent samples t-test indicated no statistically significant difference in growth between the two groups, $t(24) = 0.07$, $p = .94$.

Table 8 presents the results of the independent samples *t*-test for Math STAR growth.

Table 9

Independent Samples t-Test for Reading WIN Modality

Group	Mean Growth	SD	t	df	p
In-Person WIN	47.6	39.5			
Virtual WIN	39.3	42.8	.56	26	.58

An independent samples t-test was conducted to compare mean growth scores between students receiving in-person WIN support and those receiving virtual WIN support. Students receiving in-person WIN support demonstrated a mean growth score of 47.6 STAR points (SD = 39.5), while students receiving virtual WIN support demonstrated a mean growth score of 39.3 STAR points (SD = 42.8). The difference between groups was not statistically significant, t(26) = 0.56, p = .58, indicating that growth outcomes were similar across both intervention modalities.

Table 10

Independent Samples t-Test for Math WIN Modality

Group	Mean Growth	SD	t	df	p
In-Person WIN	18.7	39.4			
Virtual WIN	17.5	46.5	0.07	24	.94

An independent samples *t*-test was conducted to examine differences in STAR Math growth between students receiving in-person WIN support and those receiving virtual WIN support. Results indicated no statistically significant difference in growth between the two groups, $t(24) = 0.07$, $p = .94$.

Chapter Summary

This chapter presented the statistical results of the study examining academic growth within a K-12 cyber program implementing a Multi-Tiered System of Supports (MTSS) framework. Descriptive statistics were first reported to summarize student STAR Benchmark average scores and growth between the August and January assessment windows. Paired samples *t*-tests were conducted to examine overall academic growth across the sample. Independent samples *t*-tests were then used to compare growth outcomes between students receiving in-person WIN support and those receiving virtual WIN support.

The results provided quantitative evidence regarding student growth patterns and differences between intervention modalities. Interpretation of these findings, along with discussion of their implications for MTSS implementation in cyber learning environments, will be presented in Chapter 5.

Chapter 5

Discussion and Implications

Introduction

The purpose of this applied research study was to examine academic growth within a K-12 cyber program implementing a Multi-Tiered System of Supports (MTSS) framework and to evaluate the effectiveness of two intervention delivery modalities: in-person WIN (What I Need) sessions and virtual WIN sessions delivered through Microsoft Teams. Student academic growth was measured using Renaissance STAR Benchmark assessments administered during the August and January testing windows.

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

This chapter interprets the findings presented in Chapter 4 and situates them within the broader body of research on MTSS implementation, intervention systems, and online learning environments. The chapter begins with a restatement of the problem and the purpose of the study, followed by a summary of the key findings in accessible language. The results are then discussed in relation to existing research and theoretical frameworks introduced in Chapter 2. Finally, implications for educational practice are presented, along with study limitations, recommendations for future research, and concluding reflections.

Statement of the Problem

While the Multi-Tiered System of Supports (MTSS) has demonstrated effectiveness in traditional school settings, its implementation in cyber education remains less clearly understood. Virtual schools face unique challenges related to student engagement, data monitoring, communication, and intervention delivery. These structural differences raise questions about how tiered support systems function when instruction and interventions occur in online environments.

Although many cyber programs have adopted elements of MTSS, including universal screening and tiered academic support, research suggests that implementation varies widely across programs (Burns & Gibbons, 2012; Fuchs & Fuchs, 2006). While MTSS frameworks have been extensively studied in traditional brick-and-mortar school settings, the application of these systems within fully online or cyber learning environments remains less clearly defined (Barbour, 2019; Rice, 2020). In particular, limited research exists regarding whether different intervention delivery methods—such as in-person support sessions compared to virtual interventions—produce different academic outcomes for students in cyber learning environments (Ferdig et al., 2009; Rice, 2020). Without empirical evidence examining these intervention modalities, district leaders and program administrators may lack guidance for structuring effective MTSS systems that effectively support students in virtual settings.

Purpose of the Study

The purpose of this applied research study was to examine student academic growth within a K-12 cyber program implementing MTSS and to compare growth outcomes between two intervention delivery modalities: in-person WIN support and virtual WIN support. Academic growth was measured using Renaissance STAR Benchmark assessments administered during the fall semester.

Specifically, the study sought to determine:

1. Whether students enrolled in the cyber program demonstrated significant academic growth between August and January benchmark assessments.
2. Whether differences existed in academic growth outcomes between cyber students who traveled to the program's Drop-In Center to participate in in-person WIN intervention sessions and cyber students who received WIN intervention support virtually through Microsoft Teams.

By analyzing these outcomes, the study aimed to provide practical insights for school leaders and educators seeking to strengthen MTSS structures within cyber learning environments.

Summary of Findings

The results of the statistical analyses indicated that students enrolled in the cyber program demonstrated measurable academic growth between the August and January administrations of the STAR Benchmark assessments, representing growth from the beginning of the academic year through the end of the first semester. The paired-samples *t*-test revealed a statistically significant increase in STAR scores across the sample, suggesting that students experienced meaningful academic improvement during the first semester of enrollment in the cyber program.

This growth indicates that students were able to make progress in their academic performance in both reading and mathematics over time while participating in the program's instructional structure. The statistically significant change between the two benchmark periods suggests that the instructional supports, course content, and intervention structures implemented during the semester contributed to measurable gains in student achievement.

These findings provide evidence that students within the cyber learning environment were able to demonstrate academic progress during the first half of the academic year, which is an important indicator of program effectiveness within an online learning context.

When growth outcomes were compared between intervention modalities, the independent-samples t-test indicated that differences between students receiving in-person WIN support and those receiving virtual WIN support were not statistically significant. Although students participating in the in-person WIN model demonstrated slightly higher mean growth scores compared to those receiving virtual WIN support, the magnitude of this difference was relatively small and did not reach statistical significance. This finding suggests that the mode of intervention delivery alone did not substantially influence student growth outcomes within the sample. In other words, students who received targeted academic support through virtual intervention sessions via Microsoft Teams demonstrated growth patterns that were comparable to those who participated in in-person intervention sessions. The lack of statistically significant differences between the two groups suggests that both models of support were similarly effective in facilitating academic progress for students participating in the cyber program.

In practical terms, the results suggest that students participating in the cyber program demonstrated measurable academic progress over the course of the first semester and that both in-person and virtual WIN interventions were associated with positive student growth. These findings are particularly relevant within the context of cyber education, where questions often arise regarding the effectiveness of virtual instructional supports compared to traditional in-person services. The results of this study indicate that virtual intervention delivery, when implemented within a structured Multi-Tiered System of Supports (MTSS) framework, may support student learning outcomes at levels comparable to in-person intervention support. This suggests that cyber programs that incorporate structured intervention blocks, consistent progress monitoring, and targeted academic support can create learning environments that effectively promote student growth. Furthermore, the findings support the potential for flexible intervention models that combine both virtual and in-person supports to meet the diverse needs of students within cyber learning environments.

Discussion

RQ 1

To what extent did students enrolled in the cyber program demonstrate academic growth on the STAR Benchmark assessment from August to January?

The results indicated that students demonstrated statistically significant academic growth between the August and January benchmark assessments. This finding suggests that students participating in the cyber program experienced measurable improvement in academic performance during the first semester of enrollment.

These findings align with prior research indicating that Multi-Tiered System of Supports (MTSS) frameworks can support academic growth when interventions are implemented with fidelity and supported by consistent data monitoring (Balu et al., 2015; Burns & Gibbons, 2012; Fuchs & Fuchs, 2006; Freeman-Green et al., 2021; Gersten et al., 2009; McIntosh & Goodman, 2016; National Center on Intensive Intervention, 2013; Sugai & Horner, 2002). MTSS is designed to provide a structured system of increasingly intensive instructional supports that respond to student learning needs through universal screening, progress monitoring, and targeted intervention. Within this framework, educators use assessment data to identify students who may be at risk of academic difficulty and implement tiered supports intended to accelerate learning and close achievement gaps.

Research on MTSS implementation has consistently demonstrated that structured intervention systems, when paired with ongoing data analysis and progress monitoring, can lead to measurable improvements in student academic performance (Fuchs & Fuchs, 2006; Burns et al., 2015). These systems enable schools to move away from reactive models of support and instead implement proactive instructional strategies that address learning challenges earlier in the instructional process (Buffum et al., 2012). Additionally, MTSS frameworks encourage collaboration among educators, promote data-informed instructional decision-making, and provide systematic processes for adjusting interventions based on student response (Fixsen et al., 2019; Burns et al., 2015).

Within the context of cyber education, the growth observed in this study may reflect the structured implementation of MTSS practices within the program, including universal screening, weekly WIN intervention periods, and targeted academic supports based on student need. At the beginning of the academic year, students completed the Renaissance STAR Benchmark assessments, which served as a universal screening tool to identify students who may require additional academic support in reading or mathematics. These benchmark results were reviewed by teachers, instructional coaches, and program administrators to determine student placement within appropriate intervention levels and to identify specific areas of academic need.

Based on these data, students who required additional support were scheduled to participate in weekly WIN (What I Need) intervention sessions held on Wednesdays. During these sessions, students received targeted academic support designed to address the specific skill areas identified through benchmark data and ongoing progress monitoring. Some students attended these sessions in person at the program's Drop-In Center, where teachers provided direct, small-group or individualized instruction. Other students participated in WIN sessions virtually through Microsoft Teams, where teachers and instructional coaches provided targeted support using digital instructional tools, guided practice, and individualized feedback.

Throughout the semester, teachers and instructional staff continued to monitor student performance using course data, assignment completion, and ongoing assessment results within the learning management systems used by the cyber program. Instructional coaches and administrators regularly reviewed student progress data and collaborated with teachers to determine whether adjustments to intervention strategies or levels of support were needed. This ongoing cycle of data review, intervention implementation, and progress monitoring reflects the core principles of the MTSS framework and may have contributed to the academic growth observed among students during the first semester of the academic year.

Additionally, the integration of MTSS structures within the cyber program may have helped maintain instructional consistency across both online and in-person learning environments. Within the program, this consistency was supported through several coordinated practices. First, all students participated in the same universal screening process using the STAR Benchmark assessments, which provided a shared data point for teachers, instructional coaches, and administrators to identify students in need of additional support. These data were reviewed collaboratively to determine appropriate intervention needs and to guide placement into weekly WIN intervention sessions.

Second, the WIN intervention structure itself was designed to ensure that both in-person and virtual students received targeted support aligned to the same academic skill areas identified through benchmark data. Regardless of whether students attended WIN sessions in person at the Drop-In Center or participated virtually through Microsoft Teams, instructors focused on the same intervention goals and skill deficits identified through student data. Teachers and instructional staff also monitored student progress through course performance, assignment completion, and ongoing assessment data within the program's digital learning platforms. Instructional coaches and administrators supported this process by regularly reviewing student performance data and collaborating with teachers to determine whether adjustments to intervention strategies were needed. This ongoing cycle of data review, intervention planning, and instructional adjustment helped ensure that academic supports remained aligned across delivery formats and that students received consistent intervention support regardless of whether they participated in-person or virtually.

As discussed in Chapter 2, research suggests that strong Tier 1 instruction combined with targeted Tier 2 interventions can support academic progress even when instruction occurs in virtual settings (Evans et al., 2022). When supported by consistent data collection and collaborative intervention planning, MTSS frameworks may help ensure that students continue to receive appropriate academic support regardless of instructional delivery format.

While these findings demonstrate positive academic growth among students enrolled in the cyber program, it is important to acknowledge that the study design does not establish causal relationships. Rather, the results suggest an association between participation in the program's MTSS structures and observed student growth during the study period.

RQ 2

Was there a statistically significant difference in STAR Benchmark growth between students receiving in-person WIN support and those receiving virtual WIN support?

The analysis indicated that no statistically significant difference existed in growth outcomes between students receiving in-person WIN support and those receiving virtual WIN support. Although average growth scores differed slightly between the two groups, the differences were not statistically meaningful.

This finding suggests that virtual intervention delivery may provide academic support comparable to in-person intervention sessions when implemented within a structured MTSS framework. In this cyber program, the comparability of the two intervention formats was not based simply on offering both options; rather, it was supported through a shared MTSS process used across groups. All students participated in the same universal screening process through the STAR Benchmark assessments, and those data were reviewed by teachers, instructional coaches, and administrators to identify students in need of additional support. Students identified for intervention were then assigned to weekly WIN sessions held on Wednesdays, with some students traveling to the program's Drop-In Center for in-person support and others participating virtually through Microsoft Teams. Regardless of delivery format, intervention decisions were guided by the same benchmark data, the same identified skill deficits, and the same expectation that support would be adjusted in response to student performance. This approach reflects core MTSS practices that emphasize universal screening, data-based decision making, and tiered intervention structures designed to respond to student need (Burns & Gibbons, 2012; Fuchs & Fuchs, 2006; McIntosh & Goodman, 2016).

The program also promoted alignment between intervention groups through consistent monitoring of student progress using multiple data sources. In addition to the STAR benchmark windows, teachers and instructional staff reviewed course performance, assignment completion, and other indicators of academic responsiveness throughout the semester. Instructional coaches and administrators collaborated with teachers to review these data and determine whether adjustments to intervention strategies were needed. This ongoing process reflects the MTSS problem-solving model in which teams regularly analyze student data, implement targeted interventions, and adjust supports based on student response (Gersten et al., 2009; National Center on Intensive Intervention, 2013).

Within this structure, one possible explanation for the similarity in outcomes between intervention modalities is that both in-person and virtual WIN sessions were anchored to the same instructional goals, intervention materials, and data-driven decision-making processes. When core MTSS elements such as screening, targeted intervention, and progress monitoring are implemented consistently, research suggests that student academic outcomes may improve regardless of instructional setting (Balu et al., 2015; Sugai & Horner, 2002).

Another possible explanation is that virtual platforms may provide increased flexibility and accessibility for some students. In cyber learning environments, online platforms allow students to access support without the same logistical barriers associated with physical attendance, such as transportation or scheduling conflicts. Research on online and blended learning environments has suggested that the flexibility of virtual platforms can expand access to instructional support and allow programs to deliver targeted interventions to students who might otherwise face barriers to participation (Barbour, 2019; Rice, 2020).

However, these findings should be interpreted cautiously. Although the results suggest that both intervention modalities were associated with comparable academic outcomes within this program, they do not indicate that intervention delivery methods produce identical learning experiences in all contexts. Additional research examining engagement patterns, instructional strategies, and student demographics may help clarify the conditions under which different intervention modalities are most effective.

Implications for Practice

The findings of this study have several practical implications for educators, administrators, and district leaders implementing MTSS within cyber learning environments. First, the results suggest that structured intervention periods such as WIN time can support academic growth when integrated into cyber programs. Establishing consistent intervention blocks allows educators to provide targeted academic support while maintaining alignment with MTSS principles of early identification, tiered instruction, and ongoing progress monitoring. Research on MTSS implementation has emphasized the importance of dedicated intervention time within the school schedule to ensure that students receive targeted instruction aligned with identified learning needs (Burns & Gibbons, 2012; Fuchs & Fuchs, 2006; McIntosh & Goodman, 2016). Cyber programs may similarly benefit from scheduling dedicated WIN periods that provide opportunities for individualized instruction, small-group support, and systematic monitoring of student progress.

Second, the findings highlight the potential viability of virtual intervention delivery within cyber programs. The absence of statistically significant differences between intervention modalities suggests that virtual platforms may serve as effective environments for delivering targeted academic support when in-person access is limited. Prior research on online and blended learning environments has suggested that digital instructional platforms can support interactive learning, targeted feedback, and differentiated instruction when implemented within structured instructional systems (Barbour, 2019; Ferdig et al., 2009; Rice, 2020). This flexibility may be particularly important for programs serving geographically dispersed student populations or students who face transportation or scheduling constraints that limit access to in-person services.

Third, the results emphasize the importance of data-informed decision making within cyber MTSS frameworks. Consistent benchmark assessments, progress monitoring systems, and structured data review meetings allow educators to identify student needs early and adjust instructional supports accordingly. MTSS literature consistently highlights the role of universal screening and progress monitoring as key components of effective intervention systems that enable schools to respond proactively to student learning needs (Gersten et al., 2009; National Center on Intensive Intervention, 2013). Within cyber learning environments, digital dashboards and integrated data platforms may further enhance educators' ability to monitor student engagement and academic progress in real time.

Finally, district leaders implementing cyber MTSS systems may consider developing structured collaboration processes among teachers, interventionists, and support staff. Research on MTSS implementation suggests that collaborative problem-solving teams and shared data analysis processes can strengthen intervention fidelity and ensure that supports are consistently implemented across instructional settings (Burns & Gibbons, 2012; McIntosh & Goodman, 2016). Professional development focused on digital intervention strategies and collaborative data review may therefore strengthen the consistency, coordination, and sustainability of MTSS implementation in cyber learning environments.

Limitations

Several limitations should be considered when interpreting the findings of this study. First, the study was conducted within a single cyber program located in one Pennsylvania school district. As a result, the findings may not be generalizable to other cyber schools or virtual programs operating under different organizational structures, instructional models, or demographic contexts.

Second, the sample size was limited to students who had complete benchmark assessment data for both the August and December testing windows. Students with incomplete records were excluded from the analysis, which may have influenced the overall representation of the dataset and reduced the size of the analytic sample.

Third, the study relied exclusively on Renaissance STAR Benchmark assessment data to measure academic growth. Although benchmark assessments provide useful indicators of student progress and allow for consistent measurement across time points, they represent only one dimension of academic achievement and may not fully capture broader learning outcomes.

Fourth, the study examined outcomes within a relatively short time frame, focusing on academic growth during a single semester. Examining student outcomes across multiple academic years may provide additional insight into the sustained impact of MTSS interventions within cyber learning environments.

Finally, the quasi-experimental design limited the ability to control for external variables influencing student performance. Students were not randomly assigned to intervention groups; instead, group placement was influenced by factors such as scheduling, family preference, transportation, and staffing considerations. Consequently, the study identifies associations between intervention modalities and student outcomes rather than establishing causal relationships.

Recommendations for Future Research

Future research may build upon the findings of this study in several meaningful ways to further advance understanding of Multi-Tiered System of Supports (MTSS) implementation within cyber learning environments.

First, additional studies could examine MTSS implementation across multiple cyber programs or districts to better understand how program structure, student demographics, and instructional delivery models influence intervention effectiveness. The present study focused on a single district cyber program, which provided valuable insight into the relationship between intervention modality and benchmark growth within that context. However, cyber programs vary widely in terms of enrollment structures, staffing models, instructional platforms, and levels of synchronous support. Expanding the scope of research to include multiple cyber programs across different geographic regions and institutional contexts may allow researchers to identify patterns of effective MTSS implementation and determine which structural elements most strongly contribute to student success. Comparative studies across districts may also reveal how variations in staffing, intervention scheduling, or program design influence student growth within cyber learning environments.

Second, longitudinal research examining student outcomes across multiple semesters or academic years could provide deeper insight into the long-term impact of MTSS systems in virtual settings. While the current study examined growth across a single semester between benchmark assessment windows, extended research could investigate whether the academic gains observed within shorter intervention periods are sustained over time. Longitudinal analyses may also help determine whether students who receive consistent intervention support demonstrate cumulative growth across multiple grade levels or academic years. Additionally, extended studies could explore how early intervention within cyber programs affects long-term academic trajectories, including grade progression, credit accumulation, and overall program persistence.

Third, future research could expand the range of outcome variables used to measure student success within cyber learning environments. The present study relied primarily on benchmark assessment growth as an indicator of academic progress. While standardized assessments provide valuable data regarding skill development, additional indicators such as course completion rates, assignment submission patterns, student engagement metrics, attendance within synchronous learning sessions, and persistence within the program may provide a more comprehensive understanding of student outcomes. Incorporating multiple indicators of success may help researchers better understand how academic growth interacts with behavioral, motivational, and engagement factors within cyber settings.

Fourth, qualitative research examining educator and student experiences with MTSS interventions in virtual learning environments may provide valuable insight into the implementation process and perceived effectiveness of intervention models. While quantitative data can identify measurable changes in student outcomes, qualitative approaches such as interviews, focus groups, and observational studies may help illuminate how interventions are delivered in practice and how participants experience those supports. For example, future studies could explore how educators adapt intervention strategies for digital platforms, how students perceive the accessibility and usefulness of virtual support sessions, and what challenges teachers encounter when delivering differentiated instruction in cyber environments. Understanding these experiences may help refine intervention strategies and improve implementation fidelity across virtual MTSS systems.

Finally, future research could examine how culturally sustaining and culturally responsive instructional practices intersect with MTSS implementation in cyber learning environments. As discussed in Chapter 2, culturally sustaining practices emphasize the importance of recognizing and valuing students' diverse cultural identities, linguistic backgrounds, and lived experiences within instructional design. Cyber programs often serve highly diverse student populations, including students who may seek alternative learning environments due to prior academic challenges, social experiences, or personal circumstances. Investigating how culturally responsive instructional strategies, family engagement practices, and community-centered approaches can be integrated into virtual MTSS frameworks may help strengthen equity and responsiveness within cyber programs. Such research may also identify strategies that better support historically marginalized student populations within online learning contexts.

Collectively, these areas of future research have the potential to deepen understanding of MTSS implementation within cyber education and contribute to the development of more effective, equitable, and sustainable intervention systems for students learning in virtual environments.

Conclusion

This study examined academic growth within a K-12 cyber program implementing a Multi-Tiered System of Supports (MTSS) framework and compared outcomes between two intervention delivery modalities: in-person WIN (What I Need) sessions and virtual WIN sessions delivered through Microsoft Teams. The results indicated that students demonstrated measurable academic growth during the first semester of participation in the cyber program. Additionally, the analysis revealed no statistically significant differences in academic growth between students receiving in-person intervention support and those receiving virtual intervention support.

These findings suggest that cyber programs can successfully implement MTSS structures when interventions are supported by consistent data monitoring, structured intervention periods, and collaborative instructional practices. While implementing MTSS within virtual environments presents unique challenges, the results of this study highlight the potential for flexible intervention delivery models to effectively support student learning.

As cyber education continues to expand, the development of evidence-based MTSS frameworks tailored to virtual learning contexts will remain essential for ensuring equitable and effective student support. Continued research and program development may help refine intervention models, strengthen data-driven decision making, and enhance the ability of cyber programs to meet the diverse needs of students in online learning environments.

References

Al Otaiba, S., Fien, H., & Torgesen, J. K. (2019). Identifying and intervening with beginning readers who are at risk for dyslexia: Advances in individualized classroom instruction. In D. Kilpatrick (Ed.), *Reading development and difficulties* (pp. 55-78). Springer. https://doi.org/10.1007/978-3-030-26550-2_4

Al Otaiba, S., Petscher, Y., Pappamihiel, N. E., Williams, R. S., Dyrlund, A. K., & Connor, C. M. (2014). A longitudinal examination of response to intervention implementation. *Journal of Learning Disabilities, 47*(3), 224-238. https://doi.org/10.1177/0022219412453874

Archer, A. L., & Hughes, C. A. (2011). *Explicit instruction: Effective and efficient teaching*. Guilford Press.

Ardoin, S. P., Binder, K. S., Zawoyski, A. M., & Foster, T. E. (2013). The relation between data-based decision making and RTI implementation. *School Psychology Review, 42*(4), 534-550.

Aronson, B., & Laughter, J. (2016). The theory and practice of culturally relevant education: A synthesis of research across content areas. *Review of Educational Research, 86*(1), 163-206. https://doi.org/10.3102/0034654315582066

Balu, R., Zhu, P., Doolittle, F., Schiller, E., Jenkins, J., & Gersten, R. (2015). *Evaluation of response to intervention practices for elementary school reading*. National Center for Education Evaluation and Regional Assistance. https://ies.ed.gov/ncee/pubs/20154006/

Batsche, G., & Elliott, J. (2014). Creating and sustaining a culture of problem-solving and response to intervention. *Joural of Learning Disabilities, 47(2), 99-107.*

https://doi.org/10.1177/0022219413477486http://doi.org/10.1007/978-0-387-49053-3_28

Barbour, M. K. (2019). The landscape of K–12 online learning: Examining policy, practice, and research. *Journal of Online Learning Research, 5*(3), 239–246.

Batsche, G., & Tilly, W.D. (2017). Multi-tiered systems of support: A framework for school improvement. *Handbook of Response to Intervention. Springer.*

Berkeley, S., Bender, W. N., Peaster, L. G., & Saunders, L. (2020). Implementation of response to intervention: A snapshot of progress. *Journal of Learning Disabilities, 53*(2), 114-126. https://doi.org/10.1177/0022219408326214

Borup, J., Chambers, C., & Stimson, R. (2020). Online teacher and on-site facilitator perceptions of parental engagement at a supplemental virtual high school. *International Review of Research in Open and Distributed Learning, 21*(4), 79-95. https://doi.org/10.19173/irrodl.v21i4.4793https://doi.org/10.19173/irrodl.v20i2.4237

Bradshaw, C. P., Mitchell, M. M., & Leaf, P. J. (2010). Examining the Effects of Schoolwide Positive Behavioral Interventions and Supports on Student Outcomes: Results From a Randomized Controlled Effectiveness Trial in Elementary Schools: Results From a Randomized Controlled Effectiveness Trial in Elementary Schools. *Journal of Positive Behavior Interventions*, *12*(3), 133-148.

Burns, M. K., & Gibbons, K. (2012). *Implementing response-to-intervention in elementary and secondary schools*. Routledge.

Burns, M. K., Peters, R., & Noell, G. (2020). Fidelity of implementation in multi-tiered systems of support. *School Psychology Review, 49*(1), 69-82. https://doi.org/10.1016/j.jsp.2008.04.001

Castro-Olivo, S. (2014). Promoting social-emotional learning in adolescent Latino English language learners. *School Psychology Quarterly, 29*(4), 567-582. https://doi.org/10.1037/spq0000062

Choi, J., Meisenheimer, J., McCart, A., & Sailor, W. (2019). Improving learning for all students through equity-based inclusive reform practices. *Remedial and Special Education, 40*(4), 203-213.

Cook, C. R., Lyon, A. R., Kubergovic, D., Browning Wright, D., & Zhang, Y. (2015). A supportive beliefs intervention to facilitate the implementation of evidence-based practices. *Journal of School Psychology, 53*(3), 197–211

Donohoo, J. (2017). *Collective teacher efficacy: The power of educators' collective beliefs*. Corwin.

Durlak, J. A., Weissberg, R. P., Dymnicki, A. B., Taylor, R. D., & Schellinger, K. B. (2011). The impact of enhancing students' social and emotional learning. *Child Development, 82*(1), 405–432. https://doi.org/10.1111/j.1467-8624.2010.01564.x

Evans, S. W., Owens, J. S., & Bunford, N. (2022). Evidence-based psychosocial interventions for students in virtual learning environments. *Journal of Online Learning Research, 8*(2), 113-129.

Fixsen, D. L., Blase, K. A., Metz, A., & Van Dyke, M. (2019). *Implementation of science: Fidelity, predictions, and outcomes*. Active Implementation Research Network. https://www.activeimplementation.org/resources/implementation-science

Forman, S. G., & Crystal, C. D. (2015). Systems consultation for MTSS implementation. *School Psychology Review, 44*(3), 245–260.

Freeman-Green, S., Clark, M. D., & Lightner, K. (2021). Multi-tiered systems of support and culturally responsive practices: A systematic review. *Education and Treatment of*

Children, 44(3), 233-256.

Fuchs, D., & Fuchs, L. S. (2006). Introduction to response to intervention: What, why, and how valid is it? *Reading Research Quarterly, 41*(1), 93-99. https://doi.org/10.1598/RRQ.41.1.4

Gay, G. (2018). *Culturally responsive teaching: Theory, research, and practice* (3rd ed.). Teachers College Press.

Gersten, R., Compton, D., Connor, C., Dimino, J., Santoro, L., Linan-Thompson, S., & Tilly, W. (2009). Assisting students struggling with reading: Response to

Interventi

. *Institute of Education Sciences Practice Guide.*

Gregory, A., Hafen, C. A., Ruzek, E. A., Mikami, A. Y., & Allen, J. P. (2016). Closing the racial discipline gap in classrooms by changing teacher practice. *School Psychology Review, 45*(2), 171-191. https://doi.org/10.17105/SPR45-2.171-191

Guest, M., Wiley, K., & Vaden-Kiernan, N. (2024). Monitoring engagement and behavior in virtual learning environments. *Journal of Online Learning Research, 10*(1), 45-63.

Hanover Research. (2020). *Best practices in implementing MTSS in virtual and hybrid schools*. Hanover Research.

Haring Center for Inclusive Education, & Office of Superintendent of Public Instruction. (2020). *Multi-tiered system of supports: An implementation guide*. https://ippdemosites.org/wp-content/uploads/2020/11/Haring-Center-OSPI-MTSS-v2.pdf

Henderson, A. T., & Mapp, K. L. (2002). *A new wave of evidence: The impact of school, family, and community connections on student achievement*. Southwest Educational Development Laboratory.

Examining Benchmark Growth Within MTSS in a K-12 Cyber Program

Hoover, J. J., & Love, E. (2011). Supporting school improvement through MTSS. *Theory Into Practice, 50*(1), 1–7. https://doi.org/10.1080/00405841.2011.534909

Institute of Education Sciences. (2021). *Supporting students in online learning environments*. U.S. Department of Education. https://ies.ed.gov

Jagers, R. J., Rivas-Drake, D., & Borowski, T. (2018). Equity and social and emotional learning: A cultural analysis. *Educational Psychologist, 53*(2), 162-184.

Jagers, R. J., Rivas-Drake, D., & Williams, B. (2019). Transformative social and emotional learning. *American Educator, 43*(4), 18-22.

Jeynes, W. H. (2018). A meta-analysis on the effects of parental involvement on Latino students' academic outcomes. *Education and Urban Society, 50*(1), 4-33.

Lane, K. L., Kalberg, J. R., & Menzies, H. M. (2009). Developing schoolwide programs to prevent and manage problem behaviors. *Guilford Press.*

Lane, K. L., Oakes, W. P., & Menzies, H. M. (2014). Systematic screening tools for behavior disorders. *Journal of Emotional and Behavioral Disorders, 22*(3), 123–135.

McLeskey, J., & Waldron, N. (2015). Effective leadership for inclusive schools. *Journal of Special Education Leadership, 28*(2), 67–77.

McIntosh, K., & Goodman, S. (2016). *Integrated multi-tiered systems of support: Blending RTI and PBIS*. Guilford Press.

Mitchell, B. S., Stormont, M., & Gage, N. A. (2011). Tiered prevention frameworks in schools. *Education and Treatment of Children, 34*(3), 353–377.

National Education Association. (n.d.). *MTSS: More than alphabet soup*. https://www.nea.org

National Center on Intensive Intervention. (2013). *Data-based individualization: A framework for intensive intervention.* U.S. Department of Education.

OSEP Technical Assistance Center on PBIS. (2022). Positive Behavioral Interventions and Supports implementation blueprint. https://www.pbis.org

Paris, D., & Alim, H. S. (2017). *Culturally sustaining pedagogies: Teaching and learning for justice in a changing world*. Teachers College Press.Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2017). Informing progress:

Insights on personalized learning implementation. *RAND Corporation.*

Pennsylvania Training and Technical Assistance Network. (n.d.). *Multi-tiered system of support (MTSS)*. https://www.pattan.net

Renaissance Learning. (2023). *STAR Reading and STAR Math technical manuals*.

Renaissance Learning.

Rice, M. (2020). Supporting students with disabilities in K–12 online learning environments. *Educational Technology Research and Development, 68*, 2199–2213.

Rice, M., East, T., & Mellard, D. (2020)**.** Students with disabilities in K–12 online learning. *Journal of Online Learning Research, 6*(1), 37–61.

Rosen, Y., & Beck-Hill, D. (2012). Intertwining digital content and learning. *Journal of Research on Technology in Education, 45*(1), 53–64.

Sailor, W., Dunlap, G., Sugai, G., & Horner, R. (2009). Handbook of positive behavior support. *Springer.*

Skiba, R. J., Arredondo, M. I., & Rausch, M. K. (2011). *New and emerging research on disparities in discipline*. Indiana University Equity Project.

Sugai, G., & Horner, R. H. (2002). The evolution of discipline practices: School-wide positive behavior supports. *Child & Family Behavior Therapy, 24*(1-2), 23-50. https://doi.org/10.1300/J019v24n01_03

Sugai, G., Simonsen, B., Freeman, J., & La Salle, T. (2016). PBIS and systems change. School *Psychology Review, 45*(1), 20–36.

Thurlow, M., Lazarus, S., & Christensen, L. (2018). Applying MTSS for students with disabilities. *National Center on Educational Outcomes.*

Turnaround for Children. (2020). *Building student engagement and well-being in virtual learning environments*. https://turnaroundusa.org

U.S. Congress. (2015). *Every Student Succeeds Act*, 20 U.S.C. § 6301. https://www.congress.gov/bill/114th-congress/senate-bill/1177

Appendix A

Additional Statistical Tables

Table 1

Sample Reading Characteristics

Characteristic	n	Percentage
In-Person WIN	16	57.1%
Virtual WIN	12	42.9%
Total Students	28	100%
Grade K-2	11	39.3%
Grade 3-4	7	25.0%
Grade 5-6	10	35.7%

Table 2

Sample Math Characteristics

Characteristic	n	Percentage
In-Person WIN	15	57.7%
Virtual WIN	11	42.3%
Total Students	26	100%
Grade K-2	10	38.5%
Grade 3-4	6	23.1%
Grade 5-6	10	38.5%

Table 3

Descriptive Statistics for Reading STAR Benchmark Scores

Measure	Mean	Standard Deviation	Minimum	Maximum
August Reading STAR Score	1012.7	118.6	615	1150
January Reading STAR Score	1056.9	113.2	853	1178
Growth Score	44.2	56.9	-2	238

Table 4

Descriptive Statistics for Math STAR Benchmark Scores

Measure	Mean	Standard Deviation	Minimum	Maximum
August Math STAR Score	1001.4	114.8	801	1155
January Math STAR Score	1019.7	118.2	887	1164
Growth Score	18.3	42.6	-55	111

Table 5

Descriptive Statistics by Intervention Group – Reading

Group	August Mean	January Mean	Growth Mean	SD Growth
In-Person WIN	1008.9	1056.5	47.6	39.5
Virtual WIN	1017.8	1057.1	39.3	42.8

Table 6

Descriptive Statistics by Intervention Group – Math

Group	August Mean	January Mean	Growth Mean	SD Growth

In-Person WIN	999.5	1018.2	18.7	39.4
Virtual WIN	1004.1	1021.6	17.5	46.5

Table 7

Paired Samples t-Test Results for STAR Reading Growth

Variable	Mean Difference	SD	t	df	p
August vs January	+44.2	56.9	4.12	27	<.001

Table 8

Paired Samples t-Test Results for STAR Math Growth

Variable	Mean Difference	SD	t	df	p
August vs January	+18.3	42.6	2.19	25	.038

Table 9

Independent Samples t-Test for Reading WIN Modality

Group	Mean Growth	SD	t	df	p
In-Person WIN	47.6	39.5			
Virtual WIN	39.3	42.8	.56	26	.58

Table 10

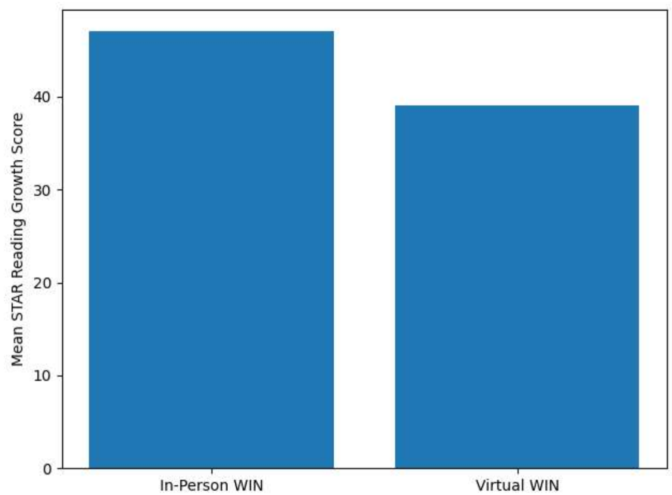
Independent Samples t-Test for Math WIN Modality

Group	Mean Growth	SD	t	df	p
In-Person WIN	18.7	39.4			
Virtual WIN	17.5	46.5	0.07	24	.94

Appendix B

Figure B1

In-Person vs. Online Reading Growth Comparison



Note. Mean STAR Reading growth scores comparing in-person WIN and virtual WIN intervention groups.

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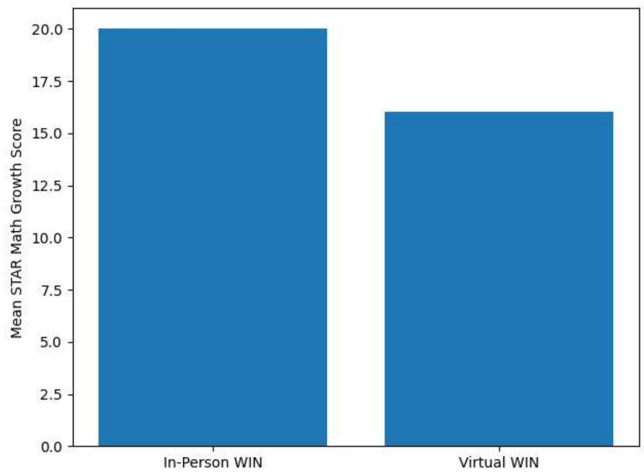
Figure B2

In-Person vs. Online Math Growth Comparison



Note. Mean STAR Math growth scores comparing in-person WIN and virtual WIN intervention groups.