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BETTER UNDERSTANDING PEOPLE'S EXPERIENCES WITH TECHNOLOGICALLY MEDIATED LEARNING, WHAT WORKS, FOR WHOM, AND WITHIN WHAT SITUATIONS: LARGE-SCALE ANALYTICS OF LEARNING EXPERIENCES AND OUTCOMES TO INFORM PRACTICE

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ABSTRACT

Aim/Purpose	This study sought to understand variations in student experiences of technologically mediated learning in the Fresno Unified School District, facilitated by its personalized learning and innovations program (PLI) and large-scale data models.
Background	While evidence supports the intentional use of information and communication technology (ICT) in learning, the focus often neglects students' social conditions, situatedness, and self-determination.
Methodology	A growth mixture model explored students' learning and revealed four distinct learning patterns: accelerating, decelerating, languishing, and thriving.
Contribution	During pandemic-era remote and hybrid teaching, this study applied Growth Mixture Modeling to identify learning trajectories among 15,135 Grade 4–6 students in a large urban school district. The research revealed how social conditions, situatedness, and self-determination shaped learning outcomes by inte-

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	grating real-time digital engagement data, assessment results, and student demographics. The findings offer practical insights for educators to personalize instruction using timely data signals and highlight how educational systems can build analytics capacity to understand better what works, for whom, and in which contexts. This work advances both research and practice by combining rigorous methodology with actionable strategies for equity-focused teaching and future-ready learning.
Findings	Data suggest the shift to remote teaching was harder for those most adept with blended instructional models, while increased support for special education and English language learners facilitated learning.
Recommendations for Practitioners	Educators can use near-real-time data to inform teaching practices that personalize student support and learning experiences while cultivating students' self-determination. Such data includes formative assessments, checks for understanding, observing writing in process, and real-time signals from interactive learning platforms, allowing students, their peers, and educators to provide appropriate and effective supports. Educational leaders can determine what interventions work better for various student groups and focus investments on high-impact programmatic interventions.
Recommendations for Researchers	Leverage the use of traditional data combined with novel signals of students' learning experiences to explore what works better for various student groups, social conditions, and situatedness. "Situatedness" reflects how technological acceptance and use are situated within the social context, social interactions, across academic content areas, and grounded in space. "Social conditions" include socio-economic status, family systems, neighborhoods, as well as classroom and school cultures.
Impact on Society	The use of near-real-time data signals from students' learning experiences supports differentiated and engaging instruction, personalized learning, and enables educators to better support students' growth in self-determination. These teacher practices better prepare students with the knowledge, skills, values, and attitudes to be ready for their futures. As demonstrated herein, education analytics can support faster improvement cycles within educational systems.
Future Research	Future research might include: (1) qualitative methods to gather students' perspectives on their learning experiences, and (2) exploration of the relationship between the quality of students' internet access and its effects on student learning experiences.

Keywords	personalized learning, large-scale analytics, self-determination, teaching practices, improvement science

INTRODUCTION

Teaching practices and students' learning experiences are increasingly mediated by information and communication technology (ICT). Evidence reveals efficacy through the intentional use of ICT (Peters et al., 2018). Yet the focus is often on the ICT-as-driver (Selwyn, 2015). This focus overlooks students' social conditions (Baxter, 2023), students' situatedness (Neufeld & Delcore, 2018), and students' self-determination (Deci & Ryan, 2000). "Situatedness" reflects how technological acceptance and use are situated within the social context with its structures of inequality, within social interactions where meaning is negotiated, across academic content areas, grounded in spaces like houses, neighborhoods, and classrooms (Neufeld & Delcore, 2018). “Social conditions” include socio-economic status, family systems, neighborhoods, and school culture.

The shift to remote learning during the pandemic accentuated certain needs as defined by self-determination theory, and these needs, when met, drive motivation and predict the level of student engagement (Chiu, 2022). These heightened needs during online learning included digital support strategies and relatedness support. This was especially important given the change in students’ situatedness (from classroom to kitchen table) and social conditions (poor performance or no internet access).

The modern world is a sociotechnical system where a person’s access to and use of ICT is both differentiated by and determinant of a person’s social, cultural, and economic capital (van Dijk, 2005). The effectiveness of technologically mediated learning experiences can improve learning outcomes (Peters et al., 2018). Further, the practice of effectively selecting and using a specific ICT that fits the learning task may also affect a student’s life trajectories and future participation in these sociotechnical systems (Warschauer, 2004; Weaver, 2022). Technology is mediated within the learning activity, and its use remains dependent upon the agency of students, educators, and students’ social networks (Shove et al., 2012). The dynamics of the learning task, while technologically mediated, are largely determined by students’ social conditions, situatedness, and self-determination. This study shows how large-scale data models can inform the ICT-mediated teaching practice and learning experience.

This study sets out to better understand the district’s remote and simultaneous teaching practices and learning experiences, through the eyes of educators and students in Grades 4-6, to document what worked well, for whom, and under what conditions. Broadly, we sought to understand:

1. Did different groups of students and educators experience remote and simultaneous learning as effective to different degrees?
2. What are the bright spots/insights (growth opportunities) for teaching and learning from students’ experiences?

The Fresno Unified School District had an enrollment of 70,000 students. Many district students lived with low income, as 89% of students’ families lived at or below 130% of the poverty level. Yet these students are all rich in potential, and this potential can be realized when they are presented with the support and necessary conditions for modern learning. The district began its blended instruction, personalized learning, and innovations program (PLI) in 2016. The aim of this program was to better prepare every student for their future with the necessary knowledge, skills, competencies, and agency (Peters et al., 2018). The theory of change (Neufeld & Ryan, 2016) was enacted through several programmatic dimensions. These included a pedagogical model and professional learning that is affective, experiential, and actionable (Langworthy et al., 2018). The conditions for modern learning also included ICT (internet, devices, apps) and related support; a community of practice that fostered impactful innovations; and large-scale learning analytics using traditional measures and novel signals (Langworthy et al., 2018; Open Education Analytics, 2022).

The pedagogical model was student-centered with differentiated instruction, cultivating skills competencies, and encouraging student agency. It engaged students with instructional models that flowed across components like whole-group instruction, followed by formative assessments or checking for understanding, targeted small-group instruction, and independent practice, and closing a lesson with collaborative practice. These models also included goal setting, reflection, and real-world projects. Teaching and learning were informed by data and the effective use of ICT. The “personalized” in PLI reflects student-centric teaching that encourages students’ choice and voice, designs learning tasks that are rigorous and relevant, adapts learning experiences that stretch and support students’ understanding, and honors students’ culture and personal strengths. A *Leader Guide* for the PLI program outlines the future-ready framework, programmatic foundations, and the program design (Neufeld & Schantz, 2024). This guide provides a maturity model for these programmatic dimensions across three core principles: equity, future-focused, and student-centered. The Leader Guide provides criteria for success for each component.

The PLI program, from its inception, included large-scale learning analytics. This learning analytics incorporates traditional measures and novel signals into a rich data model to determine what works well, for whom, and under what conditions (Langworthy & Neufeld, 2017; Open Education Analytics, 2021). The PLI program impacted over 800 educators and annually over 25,000 students. The data showed statistically significant gains on the California benchmark exams across multiple grades. These gains occurred year after year by traditionally marginalized groups (Langworthy et al., 2018). Prior to the pandemic, 20% of the district's 4,000 educators participated in PLI, with teaching practices and learning experiences situated within the classroom.

Then, the district responded to COVID-19, along with the rest of the world. The social conditions of classrooms changed as students participated in learning from within their housing units, where they experienced challenges such as social isolation and/or multiple people who were not their educators or peers learning and working within limited physical space. The situatedness of ICT use changed from the physical classroom space with working internet and devices, to the problems of internet access in, for example, low-income neighborhoods (Baxter, 2023). The "digital learning divide affecting student access" provides details on the poor quality of internet access across Fresno Unified (Neufeld, 2024). Yet, the most substantial factor for students was their self-determination and educators' support to engage students effectively (Chiu, 2022).

Educators first shifted from "in-person" to "remote teaching" and then to "simultaneous teaching" and finally back to "in-person" learning. Herein, "remote" learning refers to digital learning in which students participate synchronously from different physical locations. "Simultaneous" learning refers to synchronous learning in which some students participated from a physical classroom within a school building at the same time as other students participated remotely from different locations. References to "in-person" learning throughout indicate synchronous learning in which all students participated from the same physical classroom. Over 900 teachers practiced, to varying degrees, the PLI pedagogical model of blended teaching for personalized learning. Yet many teachers still practiced explicit direct instruction with a preference for teacher-led whole-group instruction.

The PLI team led online professional learning as educators shifted from teaching practices like PLI or explicit direct instruction to "remote teaching" and then to "simultaneous teaching." This professional learning asked teachers to consider the factors of time, space, routines, communication, and accountability, and how these factors differ between in-person and remote teaching. The differentiating factor was a student's ability to be self-directed during remote learning, a factor not as critical during in-person learning. Drew Schantz, from the Education Elements consultancy, shared this insight while working together with the district's staff to co-design the professional learning for remote teaching (personal communication, March 3, 2020). Given the ongoing shifts in teaching and learning, the district used its learning analytics model during the pandemic to determine what worked, for whom, and under what circumstances (Open Education Analytics, 2021). Herein, we document and share how we were able to capitalize on data collection infrastructure that was built before and during 2020 to make timely, data-informed, and need-driven decisions about instruction.

This study disaggregates student learning trajectories within a large, socioeconomically diverse urban district. It applies Growth Mixture Modeling to identify four distinct learning trajectories – accelerating, decelerating, languishing, and thriving – among 15,135 Grade 4–6 students in a large urban school district during pandemic-era remote and hybrid learning. By integrating real-time digital engagement data, assessment results, and student demographics, the research revealed how social conditions, situatedness, and self-determination shaped learning outcomes. It examines how instructional models like PLI, digital access quality, and socio-demographic factors interact to produce heterogeneous academic growth patterns. Furthermore, these discussions rely on latent subgroups whose experiences diverge significantly from district-wide averages.

This study bridges the gap between macro-level policy analysis and micro-level instructional realities, providing actionable evidence for educators and policymakers aiming to design equitable, responsive post-pandemic learning systems. This paper contributes to the field by:

- Application of growth mixture modeling to uncover multiple latent learning trajectories (e.g., languishing, thriving, accelerating);
- Anchoring those patterns in instructional context, digital equity variables, and social practice theory, offering a multidimensional explanation for differential learning experiences;
- Grounding findings in a district-specific analysis (Fresno Unified School District), thus contributing localized, operational insights often missing in large-scale meta-analyses.

The following section outlines the foundational theories and summarizes relevant research.

LITERATURE REVIEW

GRADUATE-READY STUDENTS

The modern vision for graduate-ready students emphasizes agency, adaptability, and future-readiness. Reports such as the American Association of School Administrators' Vision 2025 stress the importance of equipping students with skills like critical thinking, collaboration, and resilience to navigate complex future landscapes (American Association of School Administrators, 2021). Charles Fadel and Tom Vander Ark emphasize that knowledge, competencies, and character qualities such as curiosity and learner agency are foundational for future-ready learning (Fadel et al., 2015; Vander Ark, 2024; Vander Ark et al., 2020). These frameworks align closely with the Self-Determination Theory's focus on autonomy and competence. They assert that education must go beyond content mastery to empower students to own their learning pathways and thrive in an evolving digital and social environment.

SELF-DETERMINATION THEORY (SDT) AND STUDENT AGENCY IN ONLINE LEARNING

Self-Determination Theory (SDT) provides a psychological framework to understand motivation and engagement in learning environments. According to Deci and Ryan (2000), students' intrinsic motivation flourishes when their basic psychological needs – autonomy, competence, and relatedness – are supported. Wang et al. (2019) further advanced SDT through Basic Psychological Needs Theory, differentiating between the absence of need satisfaction and the presence of need frustration, and linking the latter to emotional and academic maladjustment. Bozan et al. (2024) and Shah et al. (2021) applied SDT in online learning, showing how digital environments that met these needs resulted in improved engagement and outcomes. Zhou and Zhang (2023) found that both intrinsic and extrinsic motivation influenced distance learners' performance. The growing literature, including the systematic reviews and meta-analyses, confirms the theory's enduring relevance in online contexts, especially during the pandemic (Ryan & Deci, 2019).

ICT-MEDIATED LEARNING – PROMISE AND LIMITATIONS

Technologically mediated learning environments offer unique opportunities for differentiated instruction and personalization. For example, recent quasi-experimental research in the Fresno Unified School District found that students using the Reading Progress tool experienced significantly greater reading gains than similar peers (LearnPlatform by Instructure, 2024). Reading Progress is an application that enables students to practice and record oral reading while providing educators with automated performance data on reading fluency and accuracy. ICT tools such as learning platforms, synchronous video sessions, and immediate data from assessments can support student autonomy and competency when intentionally designed. Bower (2019) introduced a comprehensive model of Technology-Mediated Learning Theory, highlighting design considerations for maximizing learning affordances. This model illustrates how thoughtful task-tool alignment can enhance engagement, cognitive load management, and meaningful learning, especially critical in post-pandemic in-person and online instruction contexts. However, Kirschner and De Bruyckere (2017) note that digital environments can undermine learning without intentional instructional design by increasing cognitive overload, fragmenting attention, and reducing metacognitive engagement. Their findings underscore that effective ICT-mediated learning requires not just access to devices and platforms but also pedagogical scaffolds that help students sustain focus, resist distractions, and process information deeply. Research shows that the impact of digital content on student well-being and learning outcomes is highly dependent on content quality. High doses of low-quality or harmful content, such as social media or fast-paced entertainment, can impair attention and mental health. Yet structured use of educational content is associated with neutral or positive effects on engagement and academic outcomes (Ghosh et al., 2024; Ryan & Deci, 2019).

These findings reinforce the importance of intentional content curation and instructional guidance when integrating technology into classrooms. However, as Selwyn (2015) critiques, edtech often carries unexamined assumptions of neutrality and can exacerbate inequality if social conditions are not addressed. Shove et al. (2012) reinforce that technological adoption must be seen through the lens of social practice. In this framework, social practices are understood as dynamic configurations of material resources, cultural meaning, and competence. Applied to learning, this means that how students and educators interact with technology depends not only on the tools themselves, but also on social routines, norms, and contexts that collectively shape technology's efficacy in real-world educational settings.

Social Practice Theory and Instructional Change

Beyond tool-task alignment, understanding how educators adopt and sustain instructional practices over time is critical to effective innovation. Social Practice Theory provides a lens for understanding how instructional behaviors become embedded through daily routines, shared norms, and situated meaning-making. According to Shove et al. (2012) and Neufeld and Delcore (2018), teaching practices, such as ICT-mediated instruction, are not merely techniques but complex social practices that integrate material arrangements (technology and space), competences (skills and strategies), and teleoaffective structures (values and goals). These practices evolve within professional learning communities, and their durability is reinforced through ongoing peer interaction, coaching, and institutional culture.

The Concerns-Based Adoption Model (CBAM) complements this sociocultural perspective by explaining how educators adopt and internalize instructional innovations over time (Hall, 1974). CBAM's Innovation Configuration Map illustrates how an innovation manifests in varied, context-sensitive ways, while its Levels of Use measures the degree of an educator's integration and adaptation of the innovation (Hall & Hord, 1987; SEDL, 2020). Educators who have deep experience with teaching innovation, such as the PLI model in this study, often exhibit higher levels of use and a more coherent innovation configuration. However, such internalization may pose challenges when educators are asked to rapidly pivot to contrasting instructional approaches, especially during disruptions such as the COVID-19 pandemic.

Digital Equity and the COVID-19 Digital Divide

The pandemic starkly revealed long-standing digital inequities. Students in low-income households disproportionately lacked access to reliable internet and devices (Baxter, 2023; Neufeld, 2024; Open Education Analytics, 2021). This created barriers not just to content but to relationships, assessment, and support. van Dijk (2005) and Warschauer (2004) frame these disparities as sociotechnical inequalities where students' digital experiences are shaped by social, cultural, and economic capital. Weaver (2022) emphasizes that true digital equity goes beyond the provision of devices to include support, training, and contextual relevance. This study revealed that students' access and use of ICT were closely correlated with socio-economic and racial demographics, highlighting how digitally mediated learning can mirror and even magnify structural inequities.

LEARNING OUTCOMES AND GROWTH MODELS

Empirical evidence confirms that the shift to online learning during the pandemic led to significant learning loss for many students, particularly in mathematics and reading. A global meta-analysis by Betthäuser et al. (2023) estimated average learning loss at 0.14 standard deviations, with disproportionately negative effects on students from disadvantaged backgrounds. Donnelly and Patrinos (2022) noted that early studies underestimated the cumulative and compounding effects of prolonged disruptions on student achievement. Supporting this, Tomasik et al. (2020) found that students in Switzerland made greater academic gains through in-person instruction compared to remote learning during school closures. Importantly, Chiu (2022) found that when students' basic psychological needs – such as autonomy, competence, and relatedness – were supported during remote instruction, their engagement improved, reinforcing the relevance of self-determination theory in digital learning contexts.

These findings underscore the need to understand not just average learning outcomes, but the diverse trajectories students followed during and after the pandemic. Georgiou et al. (2025) analyzed the development of oral and silent word reading fluency using growth modeling and found multiple distinct learning trajectories among early readers in the context of COVID-19. Their findings included students with accelerated, stable, and stagnated growth patterns, shaped by both instructional context and student characteristics. Beyond pandemic-specific analyses, Liu et al. (2016) used growth mixture modeling and latent transition analysis to track reading development from kindergarten through junior secondary school, identifying stable, low-achieving, and high-growth learners. Similarly, Mattison et al. (2023) used multivariate GMM with ECLS-K data to model reading and mathematics trajectories for students with learning disabilities, revealing both persistent low achievers and accelerated-growth groups. These studies demonstrate the analytical value of growth modeling techniques in revealing hidden heterogeneity in learning trajectories and underscore the importance of tailoring instructional supports to meet diverse student needs.

While i-Ready's longitudinal framework supports growth analysis through Typical and Stretch benchmarks (Curriculum Associates, 2025), few published studies have applied GMM directly to i-Ready data. In this district, similar learning trajectories were observed among Grades 4–6 students during the pandemic – accelerating, decelerating, languishing, and thriving. These patterns reflected not only differences in digital access, but also in instructional support, student agency, and learning models. The convergence of global, national, and local evidence highlights the need for data-driven, equity-focused interventions that align with the specific growth patterns and conditions experienced by students.

SOCIAL CONDITIONS, SITUATEDNESS, AND EDUCATIONAL TECHNOLOGY

Learning does not occur in a vacuum. As emphasized by Neufeld and Delcore (2018), the situatedness of students, whether learning at a kitchen table, a crowded room, or a well-resourced classroom, shapes the efficacy of ICT. Selwyn (2015) critiques edtech narratives that ignore context, reminding us that "digital learning always takes place somewhere." This study found that the most successful learning patterns were associated with students who had consistent educator support, access to structured learning environments, and culturally responsive pedagogy. Chiu (2022) and Shah et al. (2021) highlight that students' perceived relatedness and emotional safety influenced their academic engagement as much as access to content. The dynamics of digital tools, when embedded in daily practices (Shove et al., 2012), are shaped by social norms, economic stability, and institutional readiness. These findings stress the need for learning analytics and intervention models that consider more than just academic metrics – they must also reflect the lived experiences and environments of learners.

Research Gaps

The existing literature extensively documents pandemic-related learning loss (Betthäuser et al., 2023; Tomasik et al., 2020), inequities in digital access (Warschauer, 2004; Weaver, 2022), and the psychological foundations of student motivation in remote settings (Ryan & Deci, 2019; Shah et al., 2021). Few studies disaggregate student learning trajectories within a large, socioeconomically diverse urban district using empirical growth mixture modeling.

Prior research has not sufficiently examined how instructional models (e.g., Personalized Learning and Innovations vs. explicit direct instruction), digital access quality, and socio-demographic factors interact to produce heterogeneous academic growth patterns during and after emergency remote instruction. Furthermore, many of these discussions rely on aggregate data, overlooking the latent subgroups whose experiences diverge significantly from district-wide averages.

This paper addresses that gap by:

- applying growth mixture modeling to uncover multiple latent learning trajectories (e.g., languishing, thriving, accelerating),
- anchoring those patterns in instructional context, digital equity variables, and social practice theory, offering a multidimensional explanation for differential learning experiences, and
- grounding findings in a district-specific analysis (Fresno Unified School District), thus contributing localized, operational insights often missing in large-scale meta-analyses.

In doing so, this study bridges the gap between macro-level policy analysis and micro-level instructional realities, providing actionable evidence for educators and policymakers aiming to design equitable, responsive post-pandemic learning systems.

Methods

In order to answer these questions, this study used a large dataset that the school district had been co-developing since 2018 to understand and document the lived experiences of students and educators as they participated in remote and simultaneous learning from 2020 through 2021. A phased return to in-person learning began in April 2021 with a phase of simultaneous digital and in-person learning, followed by fully in-person learning by the end of the school year. Remote learning was conducted via digital tools and platforms, including Microsoft Teams, iReady, and Clever-accessed applications (“apps”). Clever was used as an authentication and rostering service, providing access to 3rd party digital apps. The learning outcomes data included iReady assessments on ELA (English Language Arts) and mathematics.

The Dataset (Participants, Data Sources, Measures)

The dataset for this study included all students from 4th, 5th, and 6th grades (15,135 students total) within the district. The selection of these grades was due to (1) students in primary grades K-6 have but one teacher while students in secondary grades have up to 5 teachers concurrently during an academic semester, (2) students in grades 4-6 have more schooling experience compared to the earlier grades, and (3) there was more fidelity in the administration of the iReady assessments in grades 4- 6.

There are three primary data sources:

1. District School Information System (SIS) data, including grade level, classroom roster, and in-person (physical in school) attendance,
2. learning outcome data via the iReady application, an adaptive diagnostic and individualized online instructional tool, and
3. digital engagement data consisting of video meeting attendance, chat interactions, learning document access, learning app usage, and the like via iReady, Clever, and Microsoft Teams.

While SIS data were sourced from on-premises servers, digital app data (iReady, Clever, and Microsoft Teams) were collected daily via their respective API sources:

1. Microsoft activity data: https://learn.microsoft.com/en-us/schooldatasync/data-lake-schema-activity
2. Clever data: https://support.clever.com/hc/s/articles/360049642311?language=en_US
3. iReady Export Dictionary: http://bit.ly/3UIHoY6 Digital app data are stored using Microsoft Azure cloud storage, where they are combined with SIS data and then processed for analysis.

Student data can be grouped into three main levels: student characteristics, classroom characteristics, and learning experience. Individual variables for each level are as follows:

1. Student characteristics (as measured by the district):
   a. gender (binary: male, female),
   b. ethnicity (8 categories: African American, Asian, Filipino, Hispanic, Multiple, Native American, Pacific Islander, White),
   c. language status (4 categories: Not Tested, Initially English Fluent, English Learner, Re-designated English Proficient),
   d. income status (binary: Living with Low Income, Not Living with Low Income),
   e. housing status (binary: Experiencing Homelessness, Not Experiencing Homelessness),
   f. special education eligibility (4 categories: Not Eligible, Designated Instruction/Services, Resource Specialist, Special Day Class)
2. Classroom characteristics:
   a. grade level (3 categories: 4th grade = 5169 students, 5th grade = 5123 students, 6th grade = 4843 students),
   b. school (69 categories: each school represented in the dataset, the maximum was 148 students from a single school, the minimum was 8 students, and the average was 78 students)
3. Learning experience:
   a. number of iReady ELA and mathematics lessons completed and passed (numeric),
   b. annual iReady ELA and mathematics stretch goal (numeric),
   c. time spent using Teams (continuous, normalized by classroom), and
   d. each educator's initial year of training in and implementation of ("cohort") the district's 4+ year Personalized Learning and Innovations program (PLI) (5 categories)

The iReady stretch goals are computed and reported by iReady, based on students' beginning-of-the-year performance in ELA or mathematics. These are scores assigned to each student that indicates the necessary growth to "be on track for grade-level proficiency" by the end of the year (https://www.curriculumassociates.com/access-and-equity/providing-a-path-to-proficiency-for-every-student). PLI cohort was a categorical variable coded as cohort 0 representing educators who were not implemented prior to 2020-21, and then cohorts 1-4 representing each year that PLI was implemented beginning in 2016-17 (cohort 1) through 2019-20 (cohort 4). Frequencies, means, and standard deviations for each of these variables across the entire dataset are reported in Table 1.

Prior to analysis, the dataset underwent a structured cleaning and preprocessing process. All records with a score for the first of three iReady diagnostic assessments in both ELA and mathematics were retained. The sole continuous variable (time spent using Teams) was normalized by classroom, and all nine categorical variables were dummy-coded.

Although this study focused exclusively on quantitative data, we note that qualitative data, including student and teacher interviews and open-ended survey feedback, were collected separately as part of a broader mixed-methods evaluation. These qualitative findings will be analyzed and reported in future publications to provide richer context around the patterns identified through Growth Mixture Modeling.

The Model (Analysis Approach)

We used multivariate Growth Mixture Modeling (GMM), a person-centered statistical technique designed to identify latent subgroups (or classes) within a heterogeneous population. GMM was selected for this study because it enables the identification of distinct latent subgroups of students within a heterogeneous population based on longitudinal outcome data. Unlike traditional growth models that assume a single underlying trajectory for all individuals, GMM accommodates variability by estimating multiple trajectory classes, each with its own set of growth parameters (Muthén & Muthén, 2000). This approach is particularly suited to educational research where students may experience qualitatively different learning paths. GMM was chosen over other techniques such as Hierarchical Linear Modeling (HLM) or k-means clustering because it allows for simultaneous modeling of intra-individual change over time and inter-individual differences in that change, without assuming a single population trajectory. While HLM is well-suited for analyzing nested data, it assumes a continuous distribution of individual differences, whereas our research questions investigated the possibility of qualitatively distinct subgroups. Similarly, k-means clustering, while effective for static segmentation, does not account for longitudinal structure. Therefore, GMM was best suited to capture and describe dynamic patterns of student learning over the academic year.

We operationalized our desired outcome, "learning experience," as the latent trajectory measured by the combination of iReady English language arts (ELA) and mathematics diagnostic assessments at three time points throughout the year. Administration of these measures occurred at the:

1. beginning of the school year, in August-September 2020, as fully remote assessments (Week 1),
2. middle of the year, in January-February 2021, also as fully remote assessments (Week 20), and
3. end of the year, in May 2021, as in-person assessments.

Fully remote learning was taking place from the beginning of the school year in August 2020. Simultaneous (a combination of remote and in-person) learning began in April 2021.

Due to the size of the dataset and the number of possible contributing factors, in this model, we included "time" of iReady administration, measured in weeks, as our only covariate. These parameters were used to conduct a multivariate latent class mixed model analysis to determine the number of latent trajectories present in the dataset of all 15,135 students in 4th–6th grade in the district. Also, due to the complexity of the dataset, missing data were imputed using a multiple imputation approach (detailed in Li et al., 2015) before the growth mixture model analysis (Ram & Grimm, 2009) was conducted. Model estimation was conducted in R, using the multlcmm function of the lcmm package, which uses Maximum Likelihood estimation through the Expectation-Maximization (EM) algorithm. Model selection was guided by these fit indices: log-likelihood values (LL), Bayesian Information Criterion (BIC), and Akaike Information Criterion (AIC).

After determining which model best fit the data, we then profiled each learning trajectory using a variety of data, including quantitative, usage, and demographic data, to determine the defining characteristics of each group as compared to the overall dataset. These profiles focused on the frequencies of three levels of variables within each group:

1. Student characteristics:
    a. gender (measured by the district as a binary variable),
    b. ethnicity,
    c. language status,
    d. income status,
    e. housing status, and
    f. special education eligibility

2. Classroom characteristics:
    a. grade level, and
    b. school
3. Learning experience:
    a. number of iReady ELA and mathematics lessons completed and percentage passed,
    b. annual iReady ELA and mathematics stretch goal,
    c. time spent using Teams, and
    d. exposure ("dosage") to the district's 4+ year Personalized Learning and Innovations program (PLI)

RESULTS

We discovered how much information can be extracted from the large datasets generated by online learning tools and how initiatives like Microsoft's Open Education Analytics, with which the district participated, can help analyze this data to enhance students' learning experiences. This use of data requires evolution in the district's culture around data, how it can be used, and what it means for teaching and learning in physical and digital classrooms.

We discuss these findings considering the unpredicted global need for remote learning environments during the height of the COVID-19 pandemic in 2020 – 2022. And we discuss how the use of data like these can inform novel mixes of learning modalities from remote to in-person learning.

Four distinct learning curves were found to fit the data best:

1. *accelerating learning* (increased growth occurring along with the return to in-person learning)
2. *decelerating learning* (decreased growth occurring aligned with return to in-person learning)
3. *languishing learning* (consistent learning declines across all learning environments during the whole school year), and
4. *thriving learning* (consistent, large learning gains across all learning environments during the whole school year).

For context, iReady norming tables (https://www.curriculumassociates.com/reviews/assessment/diagnostic-norms; Fall 2016 - Spring 2024) suggest that students at the 50th percentile in 4th and 5th grades are expected to experience more growth in reading during the first half of the school year than the second. In reading for 6th grade students, and in mathematics across 4th through 6th grades, students at the 50th percentile typically experience consistent growth across the school year.

These four patterns of learning are illustrated in Figures 1-4. Again, GMM was used to identify latent subgroups of students with distinct longitudinal learning trajectories. The graphs below represent the ELA and math assessment scores for each subgroup of students who are identified within each distinct longitudinal learning trajectory.

Of these four learning patterns, group 2, or decelerating learning, in which there appears to be consistent growth, but at a slow pace, as learners returned to in-person learning, was representative of the most typical learning experience in grades 4-6. Sixty-two percent of students in the dataset demonstrated this learning trajectory. The next most common learning pattern was group 1 or accelerating learning (35% of students), which also showed growth across the school year, but at an increasing pace as learners returned to in-person learning. The next two groups were quite small (2% and 1% respectively) - one demonstrating learning declines across the school year, consistently regardless of the learning environment, and the other, an even smaller group demonstrating the complete opposite - large learning gains across the school year and learning environments.

Also of note is the fact that 98% of the learners in the dataset ended the year with higher average ELA and mathematics scores than they began (groups 1, 2, and 4). The two groups with positive slopes across the entire school year (groups 1 and 4; including 36% of students in the dataset) had lower average ELA and mathematics scores at the beginning of the year than the other two groups. The decelerating learning group (62% of students in the dataset) ended the year with the highest average scores in both ELA and mathematics.

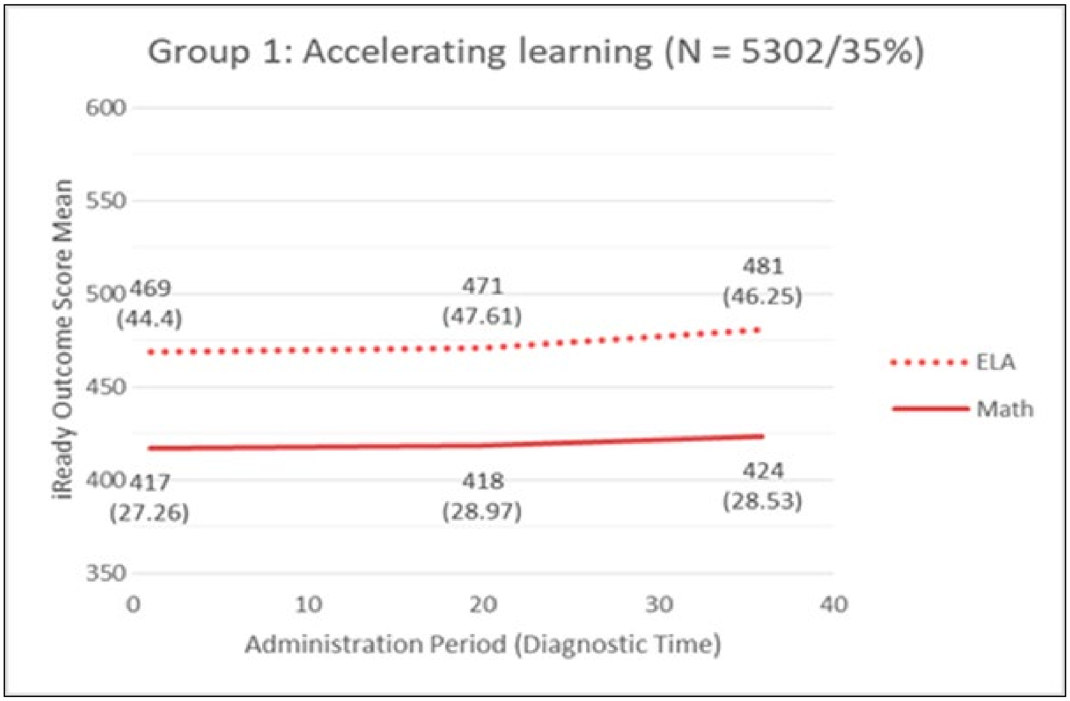

Figure 2. Mean iReady ELA and mathematics scores at each assessment time for students classified in the group that experienced accelerating learning

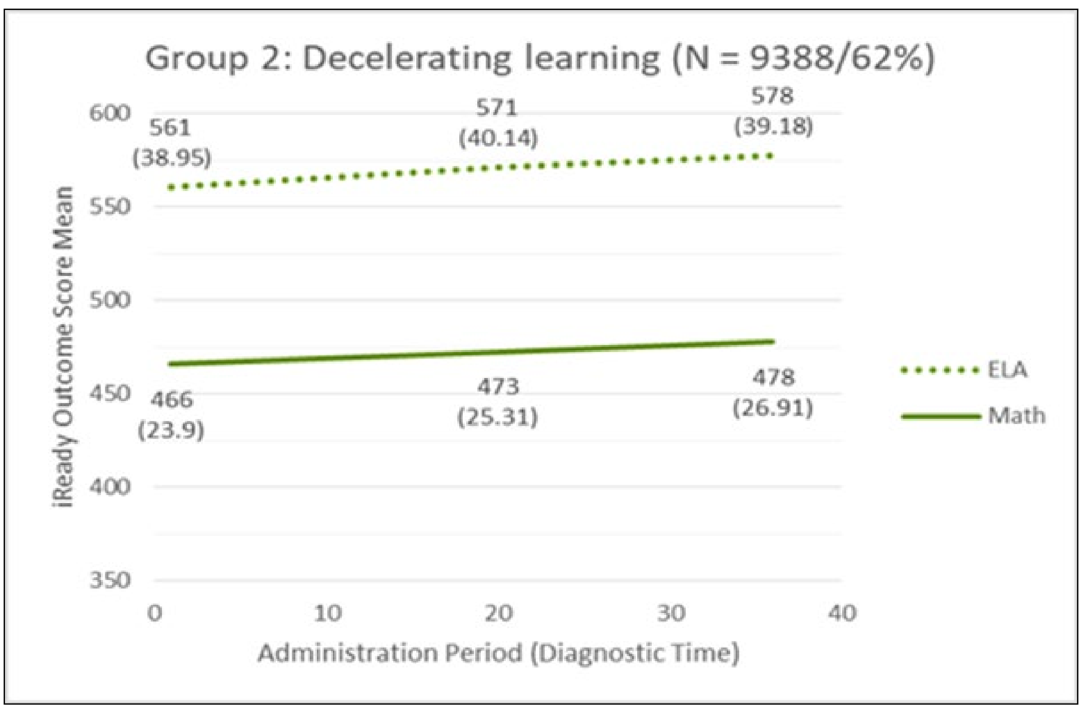

Figure 3. Mean iReady ELA and mathematics scores at each assessment time for students classified in the group that experienced decelerating learning

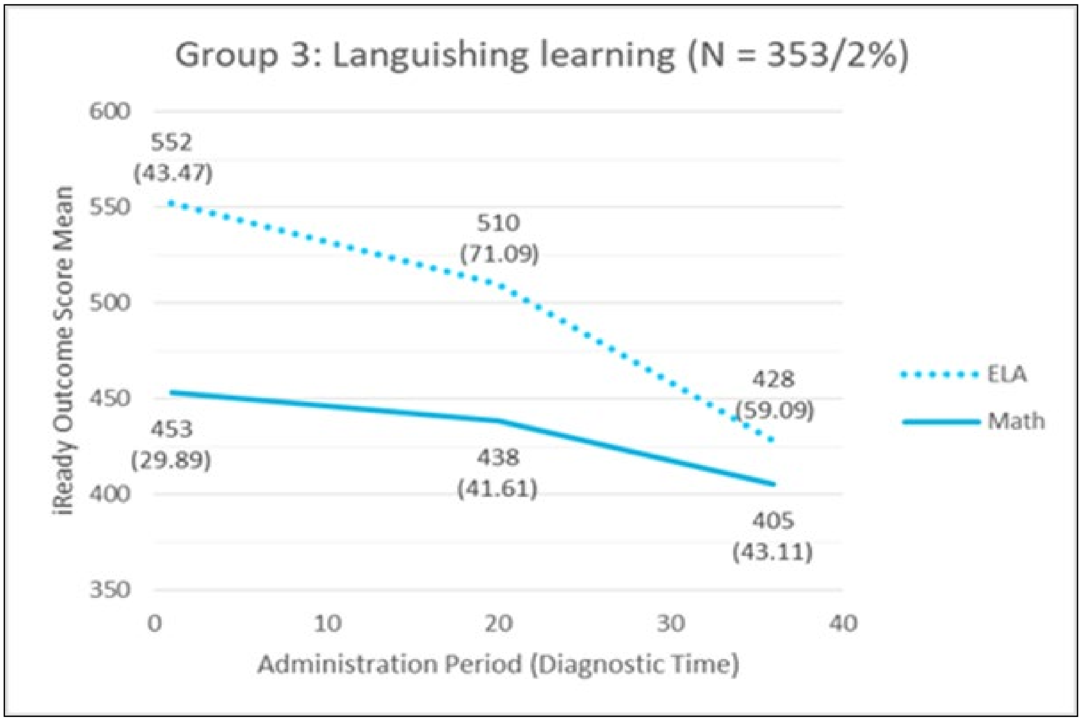

Figure 4. Mean iReady ELA and mathematics scores at each assessment time for students classified in the group that experienced languishing learning

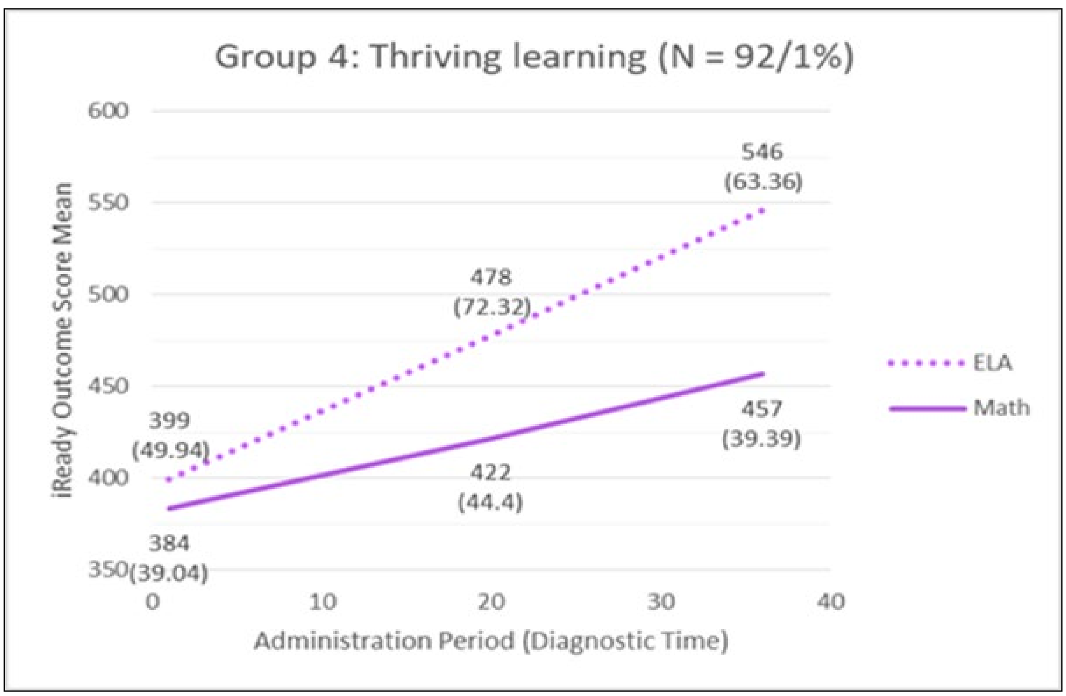

Figure 5. Mean iReady ELA and mathematics scores at each assessment time for students classified in the group that experienced thriving learning

In terms of the students experiencing each pattern of learning, there were measurable differences in their individual, classroom, and school characteristics across the four groups. These proportions are summarized in Table 1 for each group and the entire dataset as detailed below.

Table 1. Profiles of individual, classroom, and school characteristics for students in the entire dataset and each learning trajectory group

Characteristic	Entire dataset	Accelerating	Decelerating	Languishing	Thriving
Number of students	15135	5302 (35%)	9388 (62%)	353 (2%)	92 (1%)
4th Grade	34%	**47%**	27%	35%	**41%**
5th Grade	34%	33%	34%	33%	35%
6th grade	32%	20%	**39%**	32%	24%
Students' (binary) gender: Male	51.4%	56.2%	48.5%	52.4%	**66.3%**
Students' race/ethnicity					
African American	7.7%	**9.9%**	6.3%	7.9%	**20.7%**
Asian	9.9%	8.0%	11.0%	9.1%	5.4%
Filipino	0.3%	0.1%	0.4%	0.3%	0.0%
Hispanic	70.2%	**74.0%**	68.1%	71.1%	63.0%
More than one	2.9%	2.5%	3.2%	3.1%	4.3%
Native American	0.6%	0.6%	0.6%	0.6%	1.1%
Pacific Islander	0.4%	0.3%	0.4%	0.0%	0.0%
White	8.1%	4.6%	**10.0%**	7.9%	5.4%
Students' English proficiency					
Learner of English	18.9%	**34.3%**	10.0%	17.6%	**35.9%**
Redesignated fluent English proficient	19.3%	7.1%	**26.6%**	13.0%	6.5%
English proficiency never tested	59.7%	57.5%	60.6%	**67.4%**	57.6%
Proportion of students living with Low Income	88.9%	**95.7%**	84.8%	**93.5%**	**94.6%**
Students' Special Education eligibility					
Designated Instruction/Services	2.5%	3.2%	2.1%	2.8%	3.3%
Resource Specialist	6.5%	**13.4%**	2.4%	8.5%	**16.3%**
Special Day Class	3.5%	**8.7%**	0.3%	**8.5%**	**16.3%**
Not eligible	87.5%	74.6%	**95.2%**	80.2%	64.1%
Proportion of students experiencing Homelessness	0.4%	0.6%	0.3%	**1.1%**	0.0%
iReady English language arts (ELA) and mathematics data					
ELA Lessons Complete mean (SD) Pass rate (SD)	22 (26) 61% (29%)	23 (28) 72% (27%)	22 (25) 56% (27%)	**15 (23)** **52% (35%)**	**25 (41)** **74% (26%)**
Mathematics Lessons Completed mean (SD) Pass rate (SD)	20 (23) 75% (23%)	20 (24) 76% (23%)	20 (22) 75% (23%)	**15 (21)** **73% (28%)**	**25 (42)** **84% (22%)**

Characteristic	Entire dataset	Accelerating	Decelerating	Languishing	Thriving
Annual Stretch Goal ELA mean (SD)	40.4 (14.2)	**53.2 (9.28)**	**33.2 (11.04)**	**35.4 (12.33)**	**58.3 (5.39)**
Annual Stretch Goal Mathematics mean (SD)	33.8 (6.48)	**39.3 (5.2)**	**30.6 (4.82)**	33.1 (5.86)	**40.9 (5.27)**
Personalized Learning and Innovations program (PLI)					
PLI dosage mean (SD) Normalized PLI dosage mean (SD)	1.43 (2.2) 0.00 (1)	1.36 (2.15) -0.03 (0.98)	1.48 (2.23) 0.02 (1.01)	1.26 (2.11) -0.08 (0.96)	1.32 (2.06) -0.05 (0.94)
Cohort 1 (2016-17)	2.1%	2.4%	1.9%	**1.4%**	**0.0%**
Cohort 2 (2017-18)	4.6%	5.0%	4.4%	4.5%	**6.5%**
Cohort 3 (2018-19)	7.8%	**6.4%**	**8.6%**	7.9%	**5.4%**
Cohort 4 (2019-20)	13.7%	14.1%	13.7%	**9.9%**	14.1%
Cohort 0 (2020-21)	71.7%	72.1%	71.3%	**76.2%**	73.9%
Mean number of minutes students spent in Teams (SD)	118 (46)	114 (47)	120 (45)	**105 (47)**	**98 (52)**

Note: Bolded values indicate a 5% or greater difference from the expected value predicted by the equivalent statistic for the entire dataset.

Characteristics of Accelerating Learning Group

Students in the accelerating learning group were 2 to 2.5 times more likely to be eligible for certain Special Education services: 13% of students in this group were eligible for a resource specialist compared to 7% in the whole dataset; and 9% were eligible for more intensive Special Education services versus 4% in the dataset. Students in the accelerating learning group were also more likely to be a learner of English (34% of this group vs. 19% of the dataset), in the 4th grade (47% in this group versus 34% in the entire dataset), and African American (10% compared to 8%), and/or living in a low-income context (96% vs. 89%). Learners experiencing this trajectory of learning across the year were also less likely than would be predicted – again, based on the total dataset – to be in the 6th grade (20% in this group, 32% in the dataset), and not eligible for any Special Education services (75% this group vs. 88% dataset). In addition, those in this group had higher annual stretch goals (53.4 ELA; 39.3 mathematics) than the overall group on average (40.4 ELA; 33.8 mathematics); and were less likely than expected to have had educators who participated in the 2018-2019 cohort of the District's Personalized Learning and Innovations program (PLI; 6% vs. 8%). Learners in this group completed on average a similar number of iReady ELA (23) and mathematics (20) lessons as the overall group of 4th-6th graders in the dataset (22 ELA, and 20 mathematics); but spent fewer minutes on task in iReady lessons for both content areas, on average (459 vs. 516 in ELA and 472 vs. 560 in mathematics).

Characteristics of Decelerated Learning Group

In contrast, those who experienced decelerated learning were 25% more likely to be redesignated fluent speakers of English (27% in this group compared to 19% overall), 21% more likely to be in the 6th grade (39% in this group, 32% in the overall dataset), and 20% less likely to be in the 4th grade (27% vs. 34%). They were also 10-25% more likely to identify as White (10% this group, 8% in the dataset), Asian (11% vs. 10%), not eligible for any Special Education services (95% vs. 88%), and to have had educators who participated in the 2018-2019 PLI cohort (9% vs. 8%). Although students in this group spent on average ~10% more minutes on task in iReady ELA (555) and mathematics (617) lessons than the overall group (459 ELA and 560 mathematics), they completed an average number of iReady ELA (22) and mathematics (20) lessons. They also had lower annual stretch goals on average (33.2 ELA; 30.6 mathematics) than the overall group (40.4 ELA; 33.8 mathematics).

Characteristics of Languishing Learning Group:

Students who experienced languishing learning were ~2.5 times more likely to be eligible for intensive Special Education services (9% in this group as opposed to 4% in the dataset), and more than twice as likely to be in the very small group of students in the dataset experiencing homelessness (1.1% in this group, and 0.4% in the entire dataset). These students were also 30% more likely to be eligible for a resource specialist (9% in this group compared to 7% overall) and 13% more likely to never have been identified as a learner of English (67% versus 60%). They were also more likely to identify as more than one ethnicity (3.1% vs. 2.9%), and they were more likely to be living in a low-income context (94% vs. 89%). Students in this group were less likely to be redesignated English proficient (13% in this group compared to 19% overall) and less likely to identify as Asian (9% vs. 10%). Students in this group spent fewer minutes using Teams (105 vs. 118 minutes). They also spent fewer minutes on task in ELA (324) and mathematics (390). They also completed fewer (15 lessons in each content area) iReady ELA and mathematics lessons on average than those in the complete dataset (516 minutes and 22 ELA, 560 minutes and 20 mathematics). They had a lower annual stretch goal average than the overall group in iReady ELA (35.4 vs. 40.4). They were also more likely (76% vs. 72% in the whole dataset) to have educators who implemented PLI for the first time during the pandemic (in the 2020-2021 school year) and less likely to have educators who participated in the 2019-2020 cohort of PLI (10% vs. 14%).

Characteristics of Thriving Learning Group

The thriving learning group was made up of 4.5 times more students eligible for more intensive Special Education services (16% in this group versus 3.5% in the overall dataset), and at least 2.5 times more students than the overall dataset who identify as African American (21% this group, 8% in the overall dataset), and/or eligible for a Resource Specialist (16% vs. 7%). Students in this group were also more likely to be a learner of English (36% in this group compared to 19% in the dataset); identify with more than one ethnicity (4.3% vs 2.9%); identify as male gender on a binary scale (66% vs. 51%); and/or be living in a low-income context (95% vs. 89%). Like the group that experienced accelerating learning over the school year (group 1), there were more 4th grade students (41% of the group), and fewer 6th grade students (24%) in this group of students experiencing thriving learning than in the entire dataset (34% and 32% respectively). Students in this group completed on average more iReady ELA and mathematics lessons (25 in each content area), and spent more time on task in these lessons (537 minutes ELA and 532 mathematics), than the overall group, which completed on average 22 ELA lessons (516 minutes on task) and 20 mathematics lessons (560 minutes on task). However, they spent an average of only 98 minutes in Teams compared to the whole group average of 118 minutes. The average stretch goals for ELA (58.3) and mathematics (40.9) in this group were the highest of any of the four groups, and higher than the overall dataset averages of 40.4 in ELA and 33.8 in mathematics. Students in this group were almost 1.5 times more likely to have had educators who implemented PLI in the 2017-2018 school year for the first time (7% vs. 5%), and less likely to have implemented PLI in the 2018-2019 school year for the first time than all students in the dataset (5% vs. 8%).

Discussion

Interpretation of Findings

This study was designed to understand whether different groups of students experienced remote, simultaneous, and in-person instruction differently and to identify what worked well, for whom, and under what conditions. Growth Mixture Modeling (GMM) revealed four distinct learning trajectories – accelerating, decelerating, languishing, and thriving – among 15,135 Grades 4-6 students. Students were distributed unevenly across these groups, with the majority in the decelerating (62%) and accelerating (35%) groups, and smaller proportions in the languishing (2%) and thriving (1%) groups. These patterns demonstrate that student learning experiences vary not only based on instructional modality but also according to individual characteristics such as English learner status, special education eligibility, income level, and grade level.

Empirical Implications

These findings point to two central insights. First, students' learning trajectories across instructional modalities differ in patterned yet predictable ways. Second, the types of digital signals generated by students during ICT-mediated learning, such as platform engagement and lesson completion, offer educators a valuable source of timely, actionable data to support personalized learning. This suggests that real-time data systems, when implemented well, can provide educators with the insight needed to tailor supports to individual learners based on their learning activities.

Grade-level differences add further context. Students in Grade 4, who may require more adult support and redirection in learning, tend to benefit from returning to in-person environments. These students were overrepresented in the accelerating group. In contrast, Grade 6 students, who are generally more autonomous and may prefer self-paced digital formats, were more likely to show decelerating patterns as learning moved back into structured, synchronous classroom settings. These patterns suggest that developmental readiness and learner preference play a role in how students respond to shifts in instructional modality.

The accelerating and thriving groups included disproportionately higher numbers of English learners, African American students, and students with special education services. These findings challenge deficit-based assumptions and align with prior research indicating that when properly supported, students from historically underserved groups can achieve substantial academic growth (Langworthy et al., 2018). By contrast, students in the languishing group were more likely to experience homelessness or receive special education services without adequate instructional alignment. The decelerating group, which constituted the largest segment, showed reduced growth upon returning to in-person learning. One explanation for this trend may be that students who adapted to self-paced digital environments found the return to traditional classroom settings less supportive of their autonomy. This interpretation aligns with findings by Chiu (2022) and Kirschner and De Bruyckere (2017), who emphasized that students benefit from environments that support autonomy and metacognitive regulation, and that sudden shifts in modality can undermine learning in the absence of intentional scaffolds.

Theoretical Integration (Social Practice Theory and CBAM)

Contextualizing these results within the Fresno Unified School District's Personalized Learning and Innovations (PLI) program adds depth to the analysis. Launched in 2016, PLI aimed to modernize instruction through blended learning models rooted in student agency, differentiated instruction, and real-time digital feedback. By 2020, approximately 20% of educators had participated in the initiative, and more than 25,000 students were annually impacted. During the transition to remote instruction, educators trained in PLI were among the few prepared to apply pedagogical models adaptable to digital environments. Nevertheless, the relationship between PLI experience and student outcomes proved complex. Students whose teachers were part of earlier PLI cohorts appeared in both the thriving and decelerating groups, suggesting that successful adaptation depended not only on training but also on contextual and implementation variables.

Theoretical perspectives from Social Practice Theory and the Concerns-Based Adoption Model (CBAM) provide interpretive insight into these findings. According to Social Practice Theory, teaching is not simply a set of actions but a social practice composed of material arrangements, competencies, and teleoaffective structures (Neufeld & Delcore, 2018; Shove et al., 2012). Practices become embedded through professional learning and are reinforced by daily routines and professional communities. CBAM further explains the adoption of instructional innovations through components such as the Innovation Configuration Map and Levels of Use (Hall & Hord, 1987; SEDL, 2020). Educators with high Levels of Use and deeply internalized innovation configurations may have found it more difficult to pivot from student-centered, blended learning environments to synchronous, directive remote teaching. This phenomenon is akin to a seasoned cricket player being asked to switch to rugby; those with the most developed and successful practices may experience the most friction in switching domains. These dynamics highlight the need for differentiated professional support that respects instructional identity and fosters adaptive expertise.

Pedagogical and Leadership Implications

Findings also suggest the importance of dosage and implementation fidelity. Teachers who joined the PLI program during the pandemic year (cohort 0) were overrepresented among students in the languishing group, indicating that shallow or rapid adoption of complex pedagogical models may not produce desired outcomes. Conversely, students whose teachers had more sustained PLI experience were present in both the accelerating and thriving groups, albeit inconsistently. These observations support literature on innovation diffusion, which emphasizes that the effectiveness of instructional change is contingent on readiness and contextual alignment (Delcore & Neufeld, 2017).

These findings offer several practical recommendations. Schools should identify students at risk of falling into decelerating or languishing trajectories. Those transitioning between teaching modalities might be assessed for self-determination capabilities and the need for connectedness to ensure the structures and support necessary for the student's growth. Additionally, real-time learning dashboards should be employed to flag early signs of disengagement, such as reduced logins, incomplete assignments, or erratic usage patterns, enabling educators to intervene with tailored instructional and relational supports. Professional development must prioritize not only digital fluency but also pedagogical strategies that enhance autonomy, competence, and relatedness (Deci & Ryan, 2000), while accounting for the cognitive load and distractions associated with digital tools (Kirschner & De Bruyckere, 2017).

Methodological Contribution

This study also demonstrates the potential of applying Growth Mixture Modeling to educational data to uncover latent subgroups and meaningful variation in learning trajectories across large student populations. While commonly used in clinical and behavioral research, GMM is less frequently employed in district-level studies. Its capacity to identify nuanced patterns of student growth, rather than relying on single averages, makes it particularly well-suited for evaluating complex instructional environments such as those experienced during the pandemic. The integration of multiple data sources – demographics, assessment outcomes, and digital engagement metrics – enhances the ecological validity of the findings and provides a scalable approach for systems looking to move from descriptive to diagnostic analytics.

Conclusion, Limitations, and Future Work

This study identified four distinct learning trajectories – accelerating, decelerating, languishing, and thriving – among more than 15,000 upper-elementary students in a large, socioeconomically diverse school district during a year of remote, simultaneous, and in-person instruction. Using Growth Mixture Modeling on integrated learning analytics, the study found that students' progress was shaped not only by digital access and instructional modality but also by underlying conditions of social identity, learning environments, and pedagogical support. Notably, English learners and students receiving special education services were overrepresented in the accelerating and thriving trajectories – an encouraging counterpoint to deficit narratives. At the same time, students in the decelerating group experienced diminished growth when transitioning back to in-person learning, highlighting the need to understand how modality shifts interact with students' agency and instructional design.

Theoretical perspectives from Social Practice Theory and the Concerns-Based Adoption Model (CBAM) provide context for interpreting these findings. As instructional routines become embedded through professional learning and daily practice, changes in modality, particularly those requiring pedagogical shifts from student-centered to more directive instruction, can challenge even experienced educators. These dynamics reinforce the role of instructional change not only as a technical process but as a sociocultural transformation, consistent with insights from Social Practice Theory and CBAM.

Several limitations must be acknowledged:

- iReady assessment scores were administered under varied conditions – from home with caregiver supervision to in-person proctoring – complicating comparability.
- Floor effects in iReady growth metrics may have inflated perceived learning loss for some students.
- The observational design of the study precludes causal inference.
- The study did not directly capture instructional quality or home learning conditions, which likely influenced outcomes.

Despite these limitations, the study offers actionable insights grounded in robust analytic modeling and operational data.

Future research should incorporate mixed methods to explore the mechanisms behind each learning trajectory. Interviews with students, educators, and school leaders could provide insights into instructional strategies and contextual adaptations that shaped student experiences. Comparative case studies between demographically similar schools with divergent outcome profiles may reveal high-leverage practices and systemic barriers. Further exploration of the interaction between digital infrastructure, such as device access, internet speed, and learning platform design, and pedagogical strategies is also warranted.

This study demonstrates that when holistic analytics systems generate timely, actionable insights, districts, schools, and educators can move beyond reactive interventions toward responsive strategies – strengthening educator competencies, shaping dynamic learning environments to fit student needs, advancing personalized learning, and ensuring all students are better prepared for their future.

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