Impact Study of the Galt Personalized Learning Model

Betsy M. McCarthy,
WestEd

Ying Liu
University of Southern California

Suggested citation: McCarthy, B. M., & Liu, Y. (2018). *Impact study of the Galt Personalized Learning Model.* San Francisco, CA: WestEd.

WestEd is a nonpartisan, nonprofit research, development, and service agency that works with education and other communities throughout the United States and abroad to promote excellence, achieve equity, and improve learning for children, youth, and adults. WestEd has more than a dozen offices nationwide, from Massachusetts, Vermont, Georgia, and Washington, DC, to Arizona and California, with headquarters in San Francisco.

WestEd.org

Contents

Personalized Learning in the Galt Joint Union School District: Implementation and Impact 1

The Galt Model: Strengths-Based, Learner-Centered 2

Project Area 1: PLPs Mapping Pathways to College, Career, and Life 3

- PLPs 3
- Strengths-Based Learning 4
- Computer-Adaptive Assessments 5
- Learning Management System 5

Project Area 2: PL Options—From Blended Learning to Extended Learning Environments 6

- Blended Learning and Integrated Technology Opportunities 6
- Bright Future Learning Centers 6
- Extended Learning Opportunities and Project-Based Service Learning 7

Project Area 3: Systems Continuous Improvement 7

- Student Goal-Setting and Reflection 7
- Educator and Administrator Personalized Professional Learning 8
- Educator Professional Learning: CCSS, NGSS, and English Language Development 8
- Implementation Timeline and Logic Model 8
- The Impact Study 9

Method 9

The Intervention Sample 10

The MAP Suite of Assessments 10

Construction of Virtual Comparison Groups and the Reference Sample 11

The Analysis Plan 11

Results 12

Research Question 1 12

Research Question 2 13

Discussion 18

Conclusion 19

References 20

Appendix A: Timetable Showing Development and Implementation of Key Aspects of the Initiative 22

Appendix B: Logic Model Illustrating Major Activities and Projected Outcomes for the Galt Personalized Learning Initiative 23

Appendix C: The Galt Growing and Learning Together Model 24

Appendix D: Detailed Description of Data Analysis Procedures Used to Address Research Questions 1 and 2 25

LIST OF FIGURES

Figure 1. Adjusted means of treatment (in light green) and comparison (in dark green) groups over Years 1 through 4 of the intervention for mathematics. 14

Figure 2. Adjusted means of treatment (in light green) and comparison (in dark green) groups over Years 1 through 4 of the intervention for reading. 15

Figure 3. Adjusted means of treatment (in light green) and comparison (in dark green) groups over Years 1 through 3 of the intervention for language usage. 15

Figure 4. Trajectories of predicted means for treatment high-poverty and ELL subgroups for mathematics. 16

Figure 5. Trajectories of predicted means for treatment high-poverty and ELL subgroups for reading. 17

Figure 6. Trajectories of predicted means for treatment high-poverty and ELL subgroups for language usage. 17

Figure B1. Logic Model for Major Activities and Projected Outcomes for Galt Personalized Learning Initiative 23

Figure C1. The Galt Growing and Learning Together Model 24

LIST OF TABLES

Table 1. Baseline Equivalence of MAP Pre-Intervention Scores 12

Table 2. Treatment Impact Estimates for 1 Year After Full Implementation 13

Table 3. Contrast of Treatment Group Differences Over Time 14

Table A1. Timetable for Development and Implementation of Key aspects of the Initiative 22

Personalized Learning in the Galt Joint Union School District: Implementation and Impact

In 2012, the Galt Joint Union Elementary School District (GJUESD) in Galt, California was selected as one of 16 districts in the United States that received a federal Race to the Top-District grant to improve student learning through a districtwide initiative focused on *personalized learning* (PL) for students and educators. Located in California's San Joaquin Valley, Galt has a diverse population of approximately 3,900 students. To implement the 4-year initiative, the district made profound, coordinated changes to district, school, classroom, and out-of-school policies and practices. The efforts coalesced as a unique and integrated strengths-based PL model designed to support every student's strengths, aspirations, and individual learning needs.

PL, broadly defined, is a system of instructional practices that take into account individual students' needs and goals (Pane, Steiner, Baird, Hamilton, & Pane, 2017). Digital resources show great promise for supporting this approach because they include powerful tools to help identify individual students' needs and goals and to support instruction that addresses those needs and goals (Bingham, Pane, Steiner, & Hamilton, 2018). The use of PL is growing rapidly, in part because digital technologies have become more available in schools (Project Tomorrow, 2017; "Taking Stock of Personalized Learning," 2014). In addition, policies and funding supporting PL have grown significantly (U.S. Department of Education, 2017).

PL models often include the following components (Bill & Melinda Gates Foundation, 2014; Pane et al., 2017; "Taking Stock of Personalized Learning," 2014; U.S. Department of Education, 2017):

- Use of competency-based progressions: Students' progress toward clearly defined goals is continually assessed.
- Flexible learning environments: Students' needs drive the design of each individualized learning environment.

- Personal learning paths: All students follow a customized path that responds and adapts based on their individual learning progress, motivations, and goals.
- Frequent informal and formal measurement: Students' progress, areas of need, and goals are frequently measured.
- Frequently updated student profiles: All students have up-to-date records of their individual progress, needs, and goals.

This report describes a PL model developed by GJUESD, the gradual implementation of the model over a 4-year period, and the results of an impact study focused on measuring its effectiveness. The study used longitudinal student achievement data from district students, along with data from a matched virtual comparison group (VCG)—that is, a group created using a national database from a widely used assessment vendor—to measure the effect of the intervention on students in the areas of mathematics, reading, and language usage.

The Galt Model: Strengths-Based, Learner-Centered

Through the use of PL, the district aimed to shift from a proficiency model of instruction and learning to a learner-centered growth and achievement model. The initiative allowed for students from transitional kindergarten to grade 8 (TK–8) to experience PL in their classrooms and in multiple other environments. These included: (a) their school library, which was transformed into a tech-rich, extended-hours community space called a Bright Future Learning Center; (b) free after-school clubs and classes with activities focused on Common Core State Standards (CCSS) and Next Generation Science Standards (NGSS); (c) school-based and offsite outdoor service-learning activities; and (d) students' homes where, starting in Year 3 of the project, all TK–8 students and their families had continuous connectivity to technology, the district learning management system, and a host of digital resources to support learning beyond the school day.

The theoretical framework that guided the planning and implementation of the Galt PL model included activities in three interconnected project areas:

1. PL plans (PLPs) mapping pathways to college, career, and life;

2. PL options—from blended learning to extended learning environments; and
3. systems continuous improvement.

Efforts in each project area led to the development of the key aspects of the Galt PL model, which include: PLPs, strengths-based learning, computer-adaptive assessments, the use of a learning management system, blended learning and integrated technology opportunities, Bright Future Learning Centers, extended learning opportunities (including project-based service learning), student goal-setting and reflection, and educator and administrator personalized professional learning.

Project Area 1: PLPs Mapping Pathways to College, Career, and Life

Project Area 1 encompassed aspects of the model related to identifying and recording students' goals, strengths, needs, aspirations, and achievement. Assessment and growth related to academic subjects reflect competency-based progressions aligned to CCSS and NGSS. Key aspects of the model implemented under this project area, described as follows, include: PLPs, strengths-based learning, computer-adaptive assessments, and the use of a learning management system.

PLPs

PLPs, stored and accessed via the district's learning management system, are a cornerstone of the Galt PL model. The PLP is a goal-setting tool designed to facilitate frequent reflection and discussion. By capturing and reporting multiple sources of data on each student at frequent intervals, the PLP allowed students, their educators, and parents to monitor growth and set goals for achievement in specific areas. It provided features that facilitated students' involvement in and reflection on goal formulation, career, and life aspirations.

By the third year of the project, every TK–8 student had an individual PLP that was updated at least each trimester to reflect changes in student information related to learning, strengths, engagement, goal-setting, and grades. The PLP displayed information in multiple sections, including:

- **Student profile:** A section focusing on learning information, including student growth data (based on competency-based progressions aligned with CCSS), district assessment data, and engagement information (including attendance and strengths-based assessment results).

- **Goal-setting:** A section that included students' goal-setting in mathematics, reading, language usage, engagement, English language development (ELD), and project-based service-learning.
- **Performance progress:** A section that included a grade report.

Educators and students used PLPs frequently to reflect on individual student data, participated in individualized goal-setting, and planned learning activities that blended digital learning resources with face-to-face instruction to work toward students' goals. Though broad goals were updated in the PLP at least once a trimester, student reflection and goal-setting activities occurred as often as once per week.

Through the PLPs, educators, parents, and students had ongoing access to information, updated weekly, on students' progress and accomplishments. PLPs represented a shift away from the "traditional" trimester report card to an ongoing growth and achievement cycle of reflection, goal-setting, and learning.

Strengths-Based Learning

Strengths-based education involves assessing, teaching, and designing experiential learning activities to help students identify their greatest talents, then helping them develop and apply those talents to foster learning, intellectual development, and academic achievement to levels of personal excellence (Anderson, 2004). Besides a focus on individual strengths, the approach places emphasis on meaningful relationships and activities (Fox, 2008).

Galt included strengths-based learning as a foundational aspect of its PL model to further the district's efforts toward personalization and building a culture that recognizes and maximizes each individual's strengths. The district drew on research findings showing that strengths-based classroom strategies increase engagement and motivation for diverse groups of students (Greenberg et al., 2003; Lopez, 2008; Skaalvik & Hagtvet, 1990).

Galt students in grades 4 to 8, along with educators, administrators, and staff members, took the Gallup Strengths assessments, which identify each individual's three to five strongest strengths. Identified strengths were included in each student's PLP, and students' awareness of their strengths played a part in the engagement goals they set on their PLPs.

Supported by professional development in best practices for strengths-based learning, educators provided classroom activities to help students develop and apply their strengths. These efforts continued in after-school and summer extended-learning activities, which included staff trained in strengths development. Moreover, educators, administrators, and staff members often identified their own strengths publicly—for instance, on email signatures, nametags, and office signs.

Each fall, students in grades 5 to 8 also took the Gallup Student Poll, which anonymously measures hope, engagement, entrepreneurial aspiration, and career/financial literacy. Districtwide findings were then discussed by district staff and the school board, as well as at annual community outreach meetings. Results were also disaggregated by school, providing staff with a broad measure of student engagement and prompting educators and parents to engage more deeply in the multiple aspects of goal-setting on each student's PLP.

Computer-Adaptive Assessments

In each year of the Race to the Top-District initiative, all TK–8 students took the CCSS-aligned Northwest Evaluation Association (NWEA) Measures of Academic Progress (MAP) assessments in mathematics, English language arts, and language usage each trimester. These assessments are accessed by computer and are adaptive, meaning that the difficulty of each question is based on how well the student answered all of the previous questions.

Along with data from district assessments in reading and writing and from Smarter Balanced assessments in mathematics and English language arts, the MAP assessment data allowed students, educators, and families to follow students' progress on specific academic skills. In addition, data from the adaptive MAP assessments, embedded in the district's digital learning curricula, supported each student's individual blended learning experiences (see below) by allowing their online coursework to be adjusted based on current ability levels.

Learning Management System

An important part of the model is the district's comprehensive and integrated learning management system, which provided access to online resources, stored assessment data, and allowed educators and administrators to create, store, and update PLPs. This single system for performance and engagement data included issuing weekly online updates of student information to all schools and educators.
A parent portal provided parents and caregivers with anytime access to their children's ongoing activities, progress, and accomplishments.

Project Area 2: PL Options—From Blended Learning to Extended Learning Environments

Project Area 2 encompassed aspects of the Galt PL model related to: (a) integrating technology and digital resources into instruction and out-of-classroom learning, and (b) extending opportunities for learning beyond the school day. Efforts focused on providing digital and non-digital opportunities for learning in classrooms, school libraries, community settings, virtual platforms, homes, and other expanded learning environments. Key aspects of the model implemented under this project area include: blended learning and integrated technology opportunities; Bright Future Learning Centers; and extended learning opportunities, including project-based service learning.

Blended Learning and Integrated Technology Opportunities

Grant funds brought new opportunities for blended, virtual, and other types of digital learning to Galt. Blended learning involves integrating various technology tools and platforms into the learning process alongside non-digital classroom instruction to support learning. The district achieved a one-to-one student-to-device (laptop or tablet) ratio districtwide. Students took devices home to do homework and access district learning resources during out-of-school hours. For example, they could access the district's learning management system, which delivers courseware to support learning in mathematics, reading, language usage, science, and ELD.

Starting in Year 2 of project implementation, the district installed a SIM card in the devices of all students without internet access at home, allowing them anytime access to the internet and, thus, to school and classroom resources.

Bright Future Learning Centers

In the first year of the initiative, all school libraries in GJUESD were transformed into Bright Future Learning Centers. Bright Future Learning Centers are open daily—including after school and throughout the summer—at every school location to offer safe, caring, and connected learning support and opportunities. These resource- and technology-rich centers became hubs for extended learning opportunities, virtual classes, and student and parent connectivity, either at the Bright Future Learning Center or via borrowing technology for use at home.

Extended Learning Opportunities and Project-Based Service Learning

The initiative promoted year-round learning beyond the classroom by offering a wide range of free CCSS- and NGSS-focused expanded learning programs at every school in the district. These included after-school activities and clubs, school-based and offsite outdoor service-learning activities, and rich summer learning opportunities. After-school activities and summer camps included intentional connections to college and career planning, mathematics and reading support, and strengths-development, provided by support staff trained in youth development principles.

Each year, nearly all TK–8 students participated in project-based service learning. These projects took place in a range of learning spaces, including school-site outdoor nature areas, garden habitats, and the nearby nature conservancy preserve.

Project Area 3: Systems Continuous Improvement

Project Area 3 focused on applying processes, tools, and measures for continuous improvement and accountability throughout the system, including personalized evaluation processes for educators. Key aspects of the model implemented under this project area include student goal-setting and reflection and educator and administrator professional learning.

Student Goal-Setting and Reflection

Student goal-setting and reflection were a part of weekly, monthly, and trimester discussions between educators and students. The PLP was used as a goal-setting tool designed to facilitate frequent reflection and discussion. By capturing and reporting multiple sources of data at frequent intervals, students, as well as educators and parents, could monitor growth and seek or provide support as students pursued goals for achievement in specific areas.

Educator and Administrator Personalized Professional Learning

Just as each student had a PLP, each educator had a personalized professional growth plan. Created twice a year, the plan involved selecting a content or pedagogy focus area and identifying the need as well as the district strategic plan goal being addressed. Educators used a competency-based continuum to set personal learning growth goals in their focus area and to create strategies to meet those goals. Based on their plans, educators took part in personalized professional learning opportunities throughout the school year, including opportunities to attend professional learning conferences, take online courses, use online resources, or participate in professional learning communities.

Guided by a reflection rubric aligned with the competency-based continuum, administrators observed teachers both mid-year and at the end of the school year and conducted reflective conferences with each teacher. The year-end reflective conferences served as a starting point for the professional learning cycle in the new school year. Throughout the year, in addition to working with administrators, teachers used the rubric to observe, reflect with, and support each other as they deepened their PL teaching practices.

The rubric was adapted from the Educator Competencies for Personalized, Learner-Centered Teaching (Jobs for the Future) and the Council of Chief State School Officers. An analogous rubric and process were used for administrator personalized professional growth.

Educator Professional Learning: CCSS, NGSS, and English Language Development

In addition to personalized professional learning, all TK–8 educators in the district took part in professional learning related to the intervention. This included intensive training and collaboration focused on (a) implementing CCSS and (b) integrating ELD across the curriculum. The district adopted the Stanford relationships and convergences model (Cheuk, 2013) to support ELD districtwide. With the support of the Central Valley Foundation and in partnership with researchers at Stanford University, district educators received professional development focused on building their capacity to use the PL model to implement CCSS and ELD across the curriculum and to support the district's English learners. (The model is viewable at http://ell.stanford.edu/sites/default/files/VennDiagram_practices_v11%208-30-13%20color.pdf.)

Implementation Timeline and Logic Model

Each key aspect of the PL model was put into place over the first 3 years of the initiative, from fall 2013 to spring 2016. Appendix A shows a detailed timeline of when key aspects were developed and implemented. Notably, three important implementation milestones were achieved at the end of Year 2: (a) PLPs became fully functional; (b) the district implemented technological innovations so that students and families had full access to the internet and the district's learning management system during the school day, after school, and at home; and (c) all educators were trained in, and began using, research-based instructional practices related to ELD. Appendix B shows the logic model illustrating the major activities and projected outcomes for the Galt PL initiative.

By Year 4, the Galt PL model was fully in place throughout the district. In addition, the district was successfully using the model as a basis for the state's required Local Control Accountability Plan (LCAP). Appendix C shows a representation of the district's 2017–2018 LCAP goals. Titled "Growing and Learning Together," it illustrates how key aspects of the Galt PL model support efforts toward achieving the district's LCAP goals.

The Impact Study

The starting hypothesis of the initiative was that the Galt PL model would enhance students' academic achievement. In the final year of the initiative, we conducted a rigorous study, using longitudinal extant data, to test the model's effectiveness in improving achievement in mathematics, reading, and language usage. We posed two research questions:

1. Research Question 1: Impact on student achievement
    a. Is there any impact on students' academic achievement over the 4 years that include the building period (Years 1 to 3) and 1 year of full implementation of the Galt PL model? If so, what is the magnitude?
    b. Is there any impact for disadvantaged groups? In particular, is there a differential impact on high-poverty (low socioeconomic status [SES]) and English language learner (ELL) subgroups?
2. Research Question 2: Student growth trajectory
    a. What is the student growth trajectory during the years of implementation? How did change occur longitudinally?

Method

Because the Galt PL intervention was implemented districtwide, it was impossible to conduct random assignment of conditions (i.e., received the PL model vs. did not receive the PL model). As an alternative evaluation approach, therefore, we used a pre-post, quasi-experimental design with a matched "business-as-usual" comparison group. Because data included Galt students' performance on the MAP assessments, we were able to create a matched comparison group via a national database of students' performance on the MAP assessments.

In our design, we considered fall 2013 as the baseline (prior to any intervention), fall 2013 to spring 2016 (Years 1 to 3) as a "building period" during which the intervention gradually took hold, and spring 2016 to spring 2017 as the "treated" period with full implementation. Therefore, our primary interest was the change from the baseline to the post-treatment evaluation. We also planned to explore students' growth trajectories during the building period, because those might reflect any challenges that occurred during the possibly disruptive building phase and also could provide information about the possible effectiveness of particular aspects of the PL model.

The Intervention Sample

The treatment group included 2,304 students who were enrolled in kindergarten to fifth grade in GJUESD in fall 2013 and who participated in the pretest at the time. We chose this range of grade levels because younger students (i.e., pre-K) did not have valid pretest scores and older students (i.e., sixth to eighth graders) would have moved out of the district before spring 2017 and, thus, would not participate in post-testing. Among the original K to fifth graders, 393 students (17.06%) were excluded because they either left the district during the intervention period or did not participate in the post-intervention assessment. The analytic sample was balanced by gender (51% females) and majority Hispanic (60%). Most were socioeconomically disadvantaged (64%) and a large percentage were ELL (25%) at baseline.

The MAP Suite of Assessments

The MAP assessment suite (NWEA, 2017) was used in this study to evaluate students' achievement in mathematics, reading, and language usage. MAP is a widely used interim assessment system designed to measure continuous learning and growth for K–12 students. The tests are typically administered three times per academic year—fall, winter, and spring, respectively—to track students' learning as instruction progresses. The MAP scale score, referred to as the RIT score, is aligned across the full spectrum of grade levels, thus allowing cross-grade comparison (Thum & Hauser, 2015). MAP tests also align with the CCSS.

In this study, MAP tests were administered to the treatment group three times per year from fall 2013 to spring 2017, except that the Language Usage assessment was not administered in school year 2016–2017.[1] We considered the fall 2013 administration as the baseline or pre-test, and the latest available administration (i.e., spring 2017 for mathematics and reading, and spring 2016 for language usage) as the posttest. All students in the district were tested in all subjects, with the exception of kindergarteners and first graders (28% of the analytic sample), who did not take MAP language usage at the baseline.

[1] The district did not collect MAP language usage data in the 2016–2017 school year because other assessments, including SBAC, provided the district with information related to student achievement in language usage.

Construction of Virtual Comparison Groups and the Reference Sample

Matching methods are frequently used to reduce bias in causal inference (Stuart, 2010). Post-hoc construction of a matching sample usually serves as an alternative way to obtain a control group when a randomized experiment is not viable. Today, with the availability of large deidentified extant datasets from assessment vendors, new methods of creating viable, low-cost comparison groups are emerging. A "virtual" comparison group can now be created by using existing student achievement data and identifying matches for each student, thus producing a group of students that match the treatment sample on key characteristics (Ma & Cronin, 2009).

For this study, we used a k:1 nearest neighbor matching algorithm (Rubin, 1973) and relied on NWEA's national database of MAP test-takers to create such a reference sample, or VCG (Ma & Cronin, 2009). Specifically, for each student in the treatment group, we selected potential matches from the database based on: (a) grade level, (b) test subject, and (c) baseline RIT score. Potential matches also needed to come from a school with the same urban/rural classification (i.e., locale classification) and a similar free and reduced lunch program eligibility rate as the treatment students' school. Students from private or charter schools as well as other Race to the Top schools were excluded from the pool of potential matches. We considered the possibility of including other critical background variables (e.g., student's ethnicity, SES, or ELL status) as matching variables, but such information either was not readily available in NWEA's database or it placed too much restriction, leading to an untenably small size for the VCG.

The matching effort achieved our goal of creating a comparison group equivalent to the treatment group on observed pre-intervention variables in the analysis sample. Pane et al. (2017) used a similar algorithm to create a matched comparison group when investigating the efficacy of PL. Because many schools in the national database were only tested in the spring, we maximized the size of the VCG by constructing aggregated match data only for spring administration. Therefore, the MAP data analyzed in this study involved five time points—at the baseline (fall 2013) and each spring from 2014 to 2017.

The Analysis Plan

Our choice of analytic techniques was based on three considerations. First, observed intraclass correlations below .03 suggested that the interschool variability on MAP scores was almost ignorable compared to student differences within the same school. Therefore, we ignored the student-in-school structure in the analysis. Second, because the matching was only based on a handful of student- and school-level variables, and there may likely be other risk factors that were not matched, such as student-level SES and ELL status, we considered the two samples as being independent. Lastly, for other individual-level background variables, such as student's ethnicity and SES or ELL status, the reference sample consisted of aggregated matches. It was thus not feasible to construct meaningful aggregation on such covariates. Instead, we interact them with the missing data indicator, which coincided with the treatment status in our models.

To address Research Question 1, we regressed the treatment status on post-intervention scores, adjusting for covariates, including baseline MAP scores. For Research Question 2, we extended the primary model to a mixed-effect model, using all waves of spring MAP data as the dependent variable. We used the maximum likelihood estimation method to estimate the model. Appendix D provides a more detailed description of data analysis procedures used to address Research Questions 1 and 2.

Results

First, we report that the baseline equivalence of the MAP pre-intervention scores suggests that the matching was successful (see Table 1). At the baseline (fall 2013), the MAP scores were very balanced across treatment and control groups. In addition, the correlation between the baseline and the outcome MAP scores was .83 or higher.

Table 1. Baseline Equivalence of MAP Pre-Intervention Scores

	Treatment M (SD)	Control M (SD)	Standardized MDiff
Mathematics	180.2 (26.2)	180.3 (26.0)	0.00
Reading	179.1 (25.6)	179.2 (25.4)	0.00
Language usage	192.0 (19.3)	191.9 (18.9)	0.01

Source: Authors' analysis.

Research Question 1

Next, we report the study's results by research question. The first research question addressed the impact on student achievement: Is there any impact on students' academic achievement over the 4 years that include the building period (Years 1 to 3) and 1 year of full implementation of the Galt PL model? If so, what is the magnitude?

After the building period and 1 year of full implementation, the impact was positively significant for all three subjects (mathematics, reading, and language usage), with an effect size greater than .10 for each subject (see Table 2). These findings suggest that the Galt PL model intervention was effective.

Table 2. Treatment Impact Estimates for 1 Year After Full Implementation

	Treatment *N*	Treatment Adjusted *M*	Control *N*	Control Adjusted *M*	Estimated Difference	(*SE*)	95% CI	Effect Size[a]	*p* value	R^2
Mathematics	1,899	219.39	1,893	217.42	1.96	(0.42)	[1.15, 2.78]	.12	< .001	.80
Reading	1,878	212.95	1,870	211.26	1.69	(0.40)	[0.91, 2.46]	.12	< .001	.75
Language usage	1,345	213.45	1,344	212.22	1.22	(0.37)	[0.49, 1.96]	.10	.001	.79

Source: Authors' analysis.

[a]Effect sizes were calculated using Hedge's *g*, consistent with the guidance in the *What Works Clearinghouse Procedures and Standards Handbook* (Version 4.0). The mean difference is standardized by the unadjusted student-level pooled standard deviation of posttest scores. The unadjusted student-level standard deviations were 18.38 for the treatment group and 15.06 for the control group in mathematics; 15.86 for the treatment group and 12.81 for the control group in reading; and 13.52 for the treatment group and 11.17 for the control group in language usage.

The *p* value is the probability of obtaining a result at least as extreme as the one that was actually observed in a study, given that the null hypothesis is true. Effect size was measured by Hedge's *g*. In statistics, an effect size is a quantitative measure of the strength of a phenomenon.

The second part of Research Question 1 was as follows: Is there any impact for disadvantaged groups? In particular, is there a differential impact on high-poverty (low SES) and ELL subgroups?

Our analysis suggests that aspects of the model put in place in Year 2 of the building phase—including fully functional PLPs, full internet connectivity at home with access to district digital resources, and ELD implemented across the curriculum—may have been particularly effective in addressing the needs of high-poverty and ELL students. Further, though there was a dip in scores for these subgroups in Year 1, there was strong student growth in Years 3 and 4. The Year 1 dip makes results related to changes from the baseline to the post-treatment period inconclusive. However, the upward trend in Years 3 and 4 suggests that the Galt PL model, once fully in place, was effective for these subgroups. (See more on this below, under Research Question 2.)

Research Question 2

The second research question examined the student growth trajectory: What is the student growth trajectory during the years of implementation? How did changes occur longitudinally?

To address the student growth trajectory, we tracked students' academic growth from the baseline through the building years and 1 full year of implementation, after which we evaluated post-intervention outcomes. Results of our trajectory analysis suggest that after an initial dip in scores in the early building period, particularly in mathematics, the treatment group's scores in mathematics, reading, and language usage grew continuously and significantly in the remaining years. Table 3 indicates that, compared to the comparison group, the performance of the treatment group improved steadily over time. The table shows that for reading and language usage, academic achievement scores grew each year. For mathematics, achievement scores dropped slightly in 2014–2015, then grew significantly in 2015–2016 and 2016–2017.

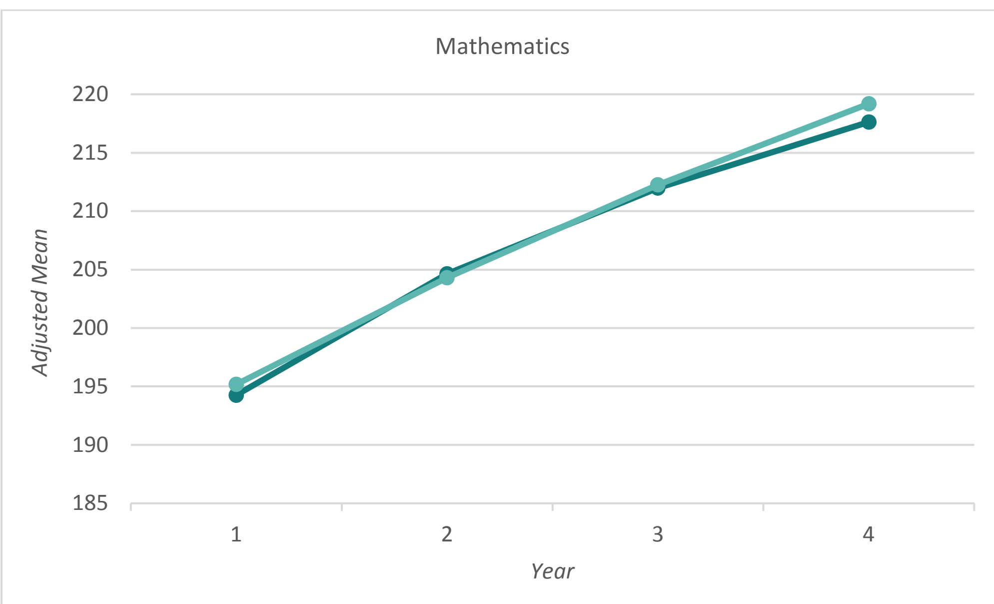
Table 3. Contrast of Treatment Group Differences Over Time

	Mathematics Est.	Mathematics SE	Mathematics p	Reading Est.	Reading SE	Reading p	Language Use Est.	Language Use SE	Language Use p
S15 vs. S14	-1.23	0.23	0.00	0.66	0.24	0.01	1.10	0.24	0.00
S16 vs. S15	0.59	0.23	0.01	0.26	0.24	0.29	0.50	.024	0.04
S17 vs. S16	1.28	0.23	0.00	1.11	.024	0.00			

Source: **Authors' analysis.**

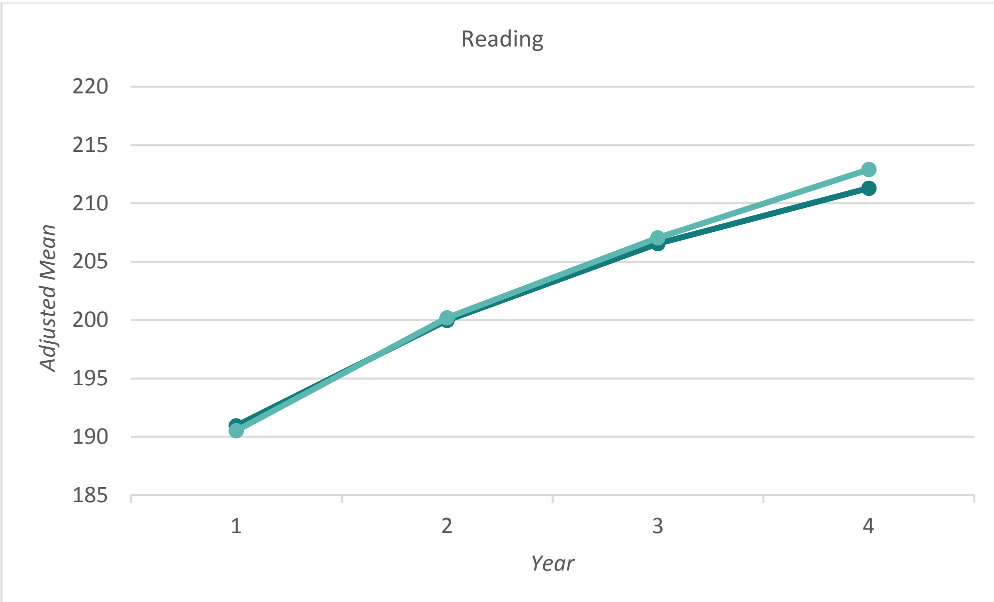
Figures 1 through 3 show the adjusted means for treatment and comparison groups over the 4 years of the building period and full intervention (Years 1 to 4 of the intervention) for mathematics, reading, and language usage.

Figure 1. Adjusted means of treatment (in light green) and comparison (in dark green) groups over Years 1 through 4 of the intervention for mathematics.



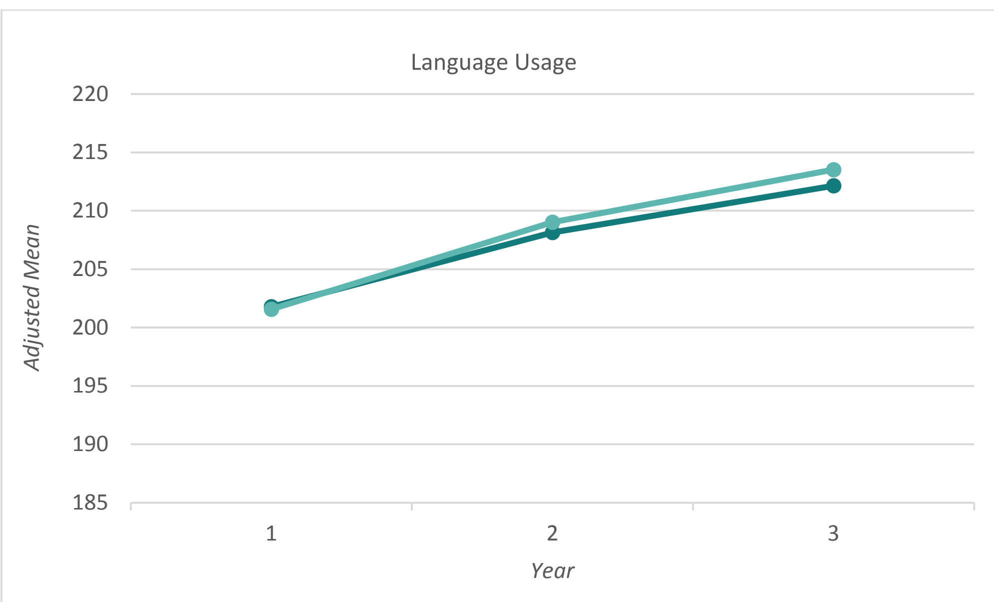
Source: **Data are from Galt Joint Union Elementary School District, with analysis by authors.**

Figure 2. Adjusted means of treatment (in light green) and comparison (in dark green) groups over Years 1 through 4 of the intervention for reading.



Source: **Data are from Galt Joint Union Elementary School District, with analysis by authors.**

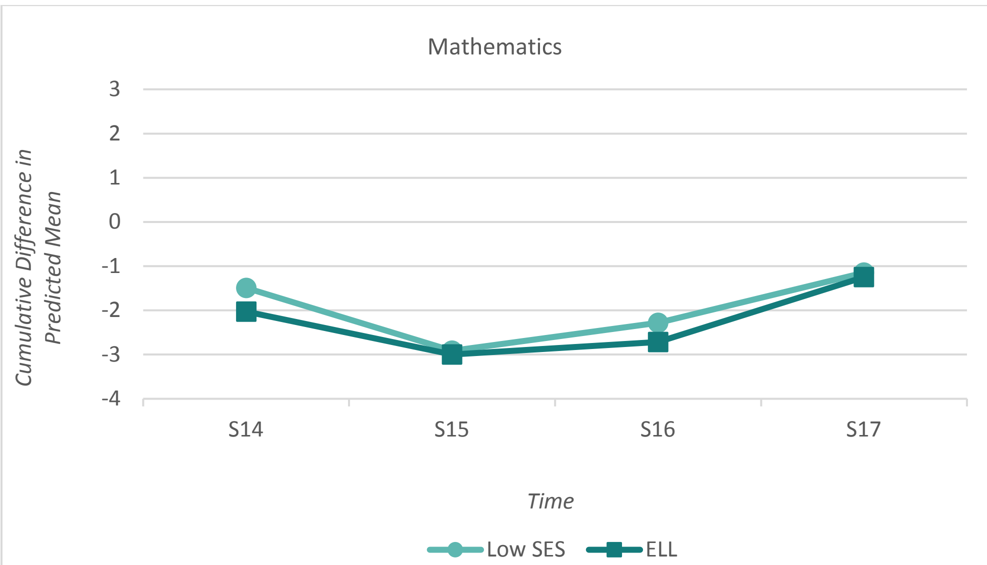
Figure 3. Adjusted means of treatment (in light green) and comparison (in dark green) groups over Years 1 through 3 of the intervention for language usage.



Source: **Data are from Galt Joint Union Elementary School District, with analysis by authors.**

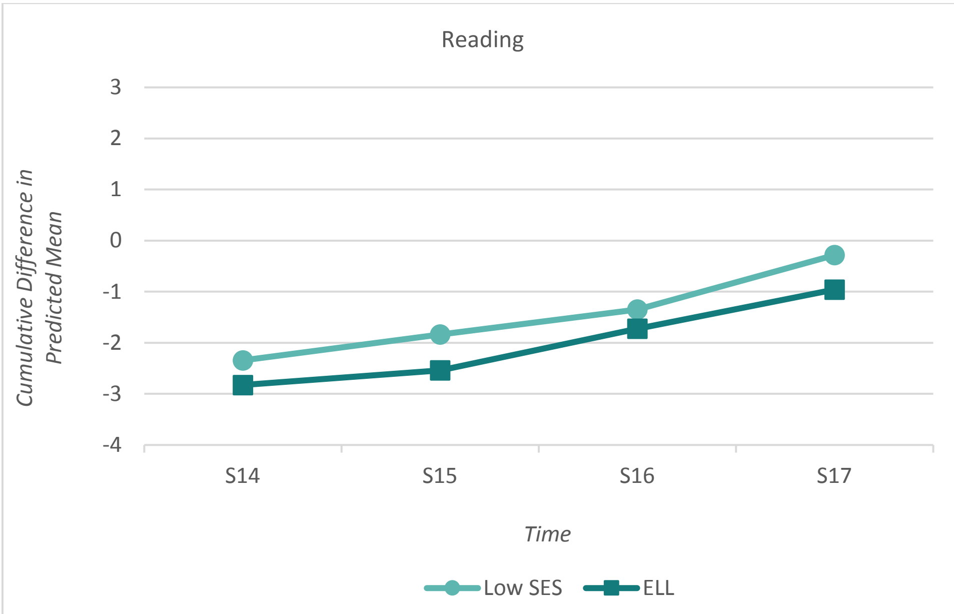
The pattern of growth for the high-poverty and ELL subgroups showed similar trends. However, as noted above, these groups' upward trends did not begin until the second year of the building phase, when many key aspects of the PL model were put into place. Starting in Year 3 for mathematics, and Year 2 for reading and language usage, these groups showed remarkable gains in achievement scores. Figure 4 through 6 show the estimated treatment group difference in mathematics, reading, and language usage for the high-poverty (low SES) and ELL subgroups, cumulated along years.

Figure 4. Trajectories of predicted means for treatment high-poverty and ELL subgroups for mathematics.



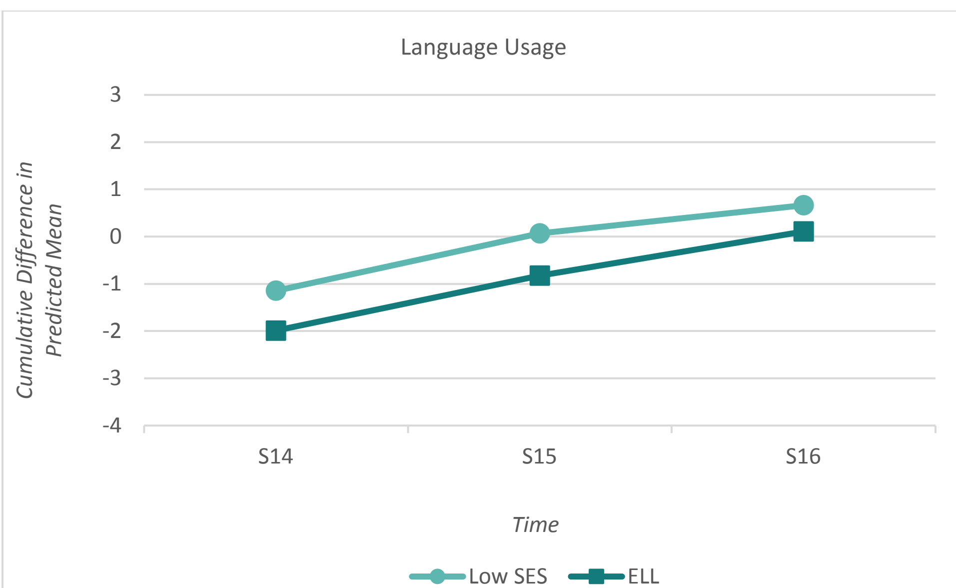
Source: **Data are from Galt Joint Union Elementary School District, with analysis by authors.**

Figure 5. Trajectories of predicted means for treatment high-poverty and ELL subgroups for reading.



Source: **Data are from Galt Joint Union Elementary School District, with analysis by authors.**

Figure 6. Trajectories of predicted means for treatment high-poverty and ELL subgroups for language usage.



Source: **Data are from Galt Joint Union Elementary School District, with analysis by authors.**

Discussion

Over a 5-year period, GJUESD created, implemented, and tested a unique PL model as part of the district's federal Race to the Top-District grant. The Galt model includes many typical PL features, such as competency-based progressions, flexible learning environments, personal learning paths, frequently updated student profiles, and frequent informal and formal measurement. But it also differs from other PL models by including a focus on strengths-based learning, which identifies and builds upon students' strengths, interests, and aspirations, allowing them to make more informed decisions when setting goals and choosing learning experiences. The Galt model also includes strengths-based PL for educators and district staff.

To test the effectiveness of the Galt model, we conducted an impact study during the final year of the initiative. The study employed a rigorous research design that involved analysis of longitudinal student achievement data from Galt students, along with corresponding data from a matched VCG of students who did not experience the intervention. The study measured the effect of the Galt model on student achievement in the areas of mathematics, reading, and language usage. In addition, it explored the model's effect on students from high-poverty families and ELLs.

Our findings suggest that the Galt strengths-based PL model is effective in supporting student learning in diverse populations in the important academic areas of mathematics, reading, and language usage. Statistical analyses showed that over the 4-year period of the intervention—including the building period Years 1 to 3 as well as Year 4, when all aspects of the model were in place—student achievement grew significantly. Statistically speaking, Galt students outpaced their matched student counterparts in academic growth by over 10 percent in each content area.

Findings for subgroup analyses also look promising for the model. After gaining full access to the model in Year 3 of the initiative, when key features were implemented—namely, PLPs, curriculum-wide ELD support, and home access to the internet and the Galt learning platforms and management system—the trajectories for students in the high-poverty and ELL subgroups turned markedly upward in all content areas, suggesting that the fully implemented model supports achievement for these subgroups.

The matching method (i.e., VCGs) used in this study is new and innovative. However, it is yet to be determined to what extent it is comparable to, or different from, popular methods such as propensity score matching. A natural next step is to construct different "reference" samples based on alternative matching methods and conduct a sensitivity analysis to examine the robustness of the findings.

The results of the current study are notable for several reasons. Millions of dollars are spent each year to develop interventions and strategies that will promote student learning in diverse student populations. In most cases, these efforts are not successful in significantly improving outcomes for students. This study suggests that a PL model can support student achievement in diverse and historically underperforming populations. Many successful interventions focus on one particular subject area. The finding that growth occurred across all three academic domains suggests that something powerful may be occurring at the student level of interaction that affects the way students approach the curriculum.

In addition, the district's innovative methods for addressing non-academic aspects of learning may be contributing to students' motivation and engagement in learning. The model's focus on attending and responding to students' strengths, specific attention to the need for ELD, and intentional use of student goal-setting may have each contributed to the students' access and response to curricula. The results suggest that further study is warranted to explore the key mechanisms in the model and how they contribute to academic achievement in diverse and historically underperforming populations.

Conclusion

This study contributes to the growing literature in the field of PL by contributing evidence related to a successful PL model. The study describes the innovative Galt PL model, which builds on past models that focused on individualized digital learning along with competency-based progressions, flexible learning environments, personal learning paths, and frequently updated student profiles. The Galt PL model builds on these earlier versions of PL to include strengths-based learning features, which may contribute to students' motivation, engagement, and ability to access and persevere in the curriculum. The study also builds on the growing practice of using VCGs to study educational interventions (Pane et al., 2017). VCG designs can be relatively low cost and allow for rigorous studies of educational interventions when randomization is not practical or possible. Overall, this study's findings will be valuable to educators, researchers, and policymakers.

References

Anderson, E. C. (2004). *What is strengths-based education? A tentative answer by someone who strives to be a strengths-based educator.* Unpublished manuscript.

Bill & Melinda Gates Foundation. (2014, November). *Early progress: Interim research on personalized learning*. Retrieved from http://k12education.gatesfoundation.org/wp-content/uploads/2015/06/Early-Progress-on-Personalized-Learning-Full-Report.pdf

Bingham, A., Pane, J., Steiner, E., & Hamilton, L. (2016). Ahead of the curve: Implementation challenges in personalized learning school models. *Educational Policy, 32*(3), 454–489. doi:10.1177/0895904816637688

Cheuk, T. (2013). *Relationships and convergences among the mathematics, science, and ELA practices*. Palo Alto, CA: Stanford University.

Fox, J. (2008). *Your child's strengths: A guide for parents and teachers*. London, United Kingdom: Penguin Press.

Greenberg, M. T., Weissberg, R. P., O'Brien, M. U., Zins, J. E., Fredericks, L., Resnick, H., & Elias, M. J. (2003). Enhancing school-based prevention and youth development through coordinated social, emotional and academic learning. *American Psychologist, 58*, 466–474. doi:10.1037/0003-066X.58.6-7.466

Lopez, S. (2008). *Positive psychology: Exploring the best in people: Discovering human strengths* (Vol. 1). New York, NY: Praeger.

Lopez, S., & Louis, M. (2010). The principles of strength-based education. *Journal of College and Character, 10.* doi:10.2202/1940-1639.1041

Ma, L., & Cronin, J. (2009). *Evaluating the effect of random selection on virtual comparison group creation*. Retrieved from Northwest Evaluation Association website: https://www.nwea.org/content/uploads/2014/08/EVALUATING-THE-EFFECT-OF-RANDOM-SELECTION-ON-VIRTUAL-COMPARISON-GROUP-CREATION.pdf

McCarthy, B., & Liu, Y. (in press). *Impact study of the Galt Personalized Learning Model*. Retrieved from wested.org.

Northwest Evaluation Association. (2017). *Measures of Academic Progress (MAP): Interim assessments for K–12*. Retrieved from https://www.nwea.org/content/uploads/2015/09/MAP-Comprehensive-Brochure-Jan17.pdf

Pane, J. F., Steiner, E. D., Baird, M. D., Hamilton, L. S., & Pane, J. D. (2017, July 11). *Informing progress: Insights on personalized learning implementation and effects*. Retrieved from RAND Corporation website: https://www.rand.org/pubs/research_reports/RR2042.html

Personalized learning: Vision vs reality. (2017, November). *Education Week*. Retrieved from http://www.edweek.org/ew/collections/personalized-learning-Full-report-2017.pdf

Project Tomorrow. (2017). *National* d*ata from the 2017 Speak Up Teacher Survey*. Retrieved from Project Tomorrow at https://tomorrow.org/

Rubin, D. B. (1973). Matching to remove bias in observational studies. *Biometrics, 29*, 159–184. doi:10.2307/2529684

Rubin, D. (2007). The design versus the analysis of observational studies for causal effects. *Statistics in Medicine*, *26*, 20–36. doi:10.1002/sim.2739

Skaalvik, E. M., & Hagtvet, K. W. (1990). Academic achievement and self-concept: An analysis of causal predominance in developmental perspective*. Journal of Personality and Social Psychology, 58*, 292–307. doi:10.1037/0022-3514.58.2.292

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science, 25*(1), 1–21. doi:10.1214/09-STS313

Taking stock of personalized learning. (2014, October). *Education Week*. Retrieved from http://www.edweek.org/ew/collections/personalized-learning-special-report-2014/index.html

Thum, Y. M., & Hauser, C. H. (2015, November 6). *NWEA 2015 MAP norms for student and school achievement status and growth*. Retrieved from Northwest Evaluation Association website: https://www.nwea.org/content/uploads/2018/01/2015-MAP-Norms-for-Student-and-School-Achievement-Status-and-Growth.pdf

U.S. Department of Education, Office of Educational Technology. (2017, January). *Reimagining the role of technology in education: 2017 National Education Technology Plan update*. Retrieved from https://tech.ed.gov/files/2017/01/NETP17.pdf

Appendix A: Timetable Showing Development and Implementation of Key Aspects of the Initiative

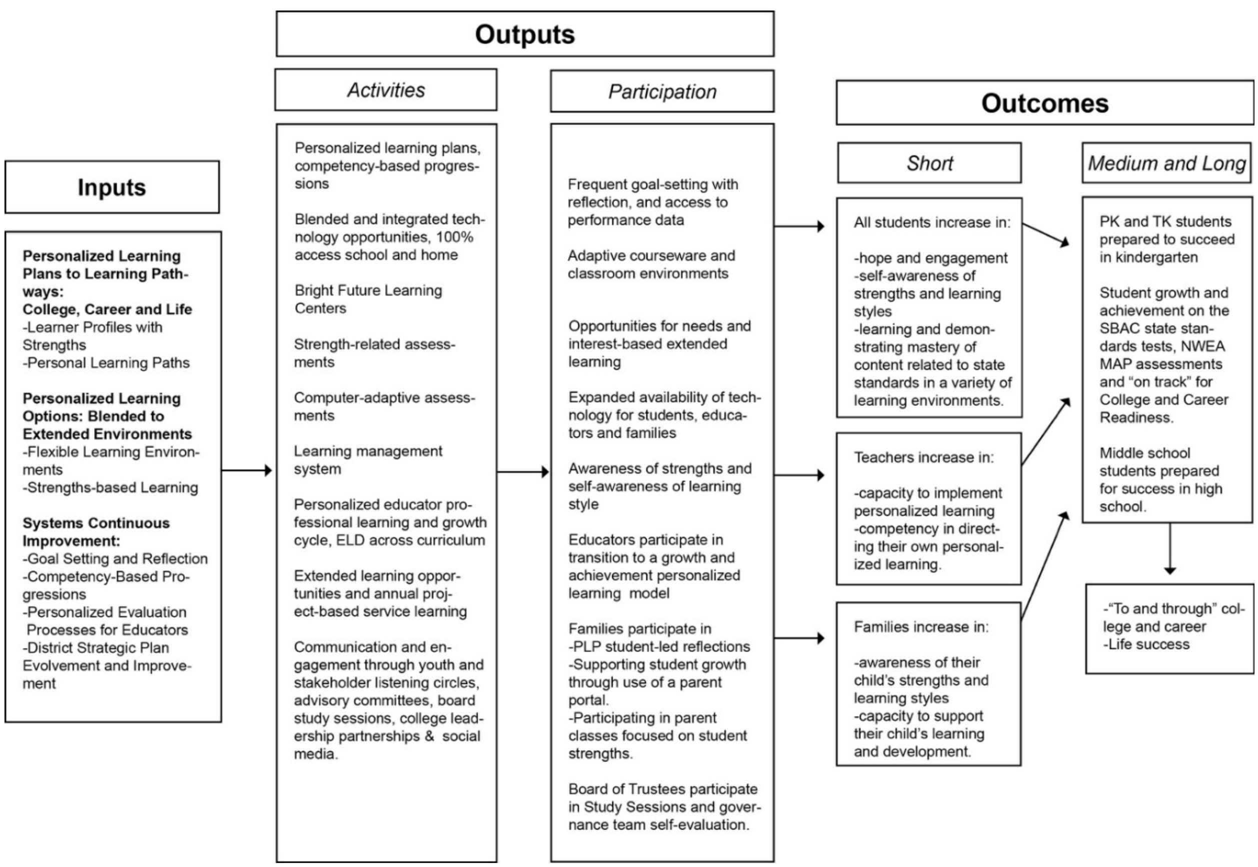
Table A1. Timetable for Development and Implementation of Key aspects of the Initiative

Year	Key Aspect
Year 1	• All GJUESD employees take Strengths Quest Assessment identifying top five strengths or talents • All GJUESD educators receive a laptop • Early PLP created, tested, and used in TK–3 • Strengths assessment and Student Poll implemented • First wave of technology implementation in schools and BFLCs • First learning platforms put into place in some classrooms and BFLCs • Early after-school programming begins at schools • CCSS educator professional development • Project-based service-learning implemented in classrooms and after-school
Year 2	• First version of the PLP is fully functional for students TK–8 with ELD goal-setting • Technology and learning platform expansion begins to provide connectivity to all students at schools, BFLCs, and home environments • After-school programming begins at schools • Preschool home visitations • CCSS professional development • Intensive ELD professional development and practice of the Stanford Relationships and Convergences Model (Cheuk, 2013) across the curriculum begins • Learning management system gains functionality
Year 3	• Technology and learning platform expansion provides connectivity to all students at school, BFLCs, and home environments • Intensive ELD professional development and practice across the curriculum fully implemented across district • Educator personalized learning including goal-setting, planning, classroom visits and reflection with administrator, peer observation, and rubric reflection • CCSSO teaching standards for personalization • Personalized after-school and summer programming fully functional • Assessments and professional development for strengths-based learning • Learning management system fully functional • GJUESD Facilities Master Plan adopted by board aligning with personalization
Year 4	• Full Implementation of all aspects of the project

Source: **Authors.**

Appendix B: Logic Model Illustrating Major Activities and Projected Outcomes for the Galt Personalized Learning Initiative

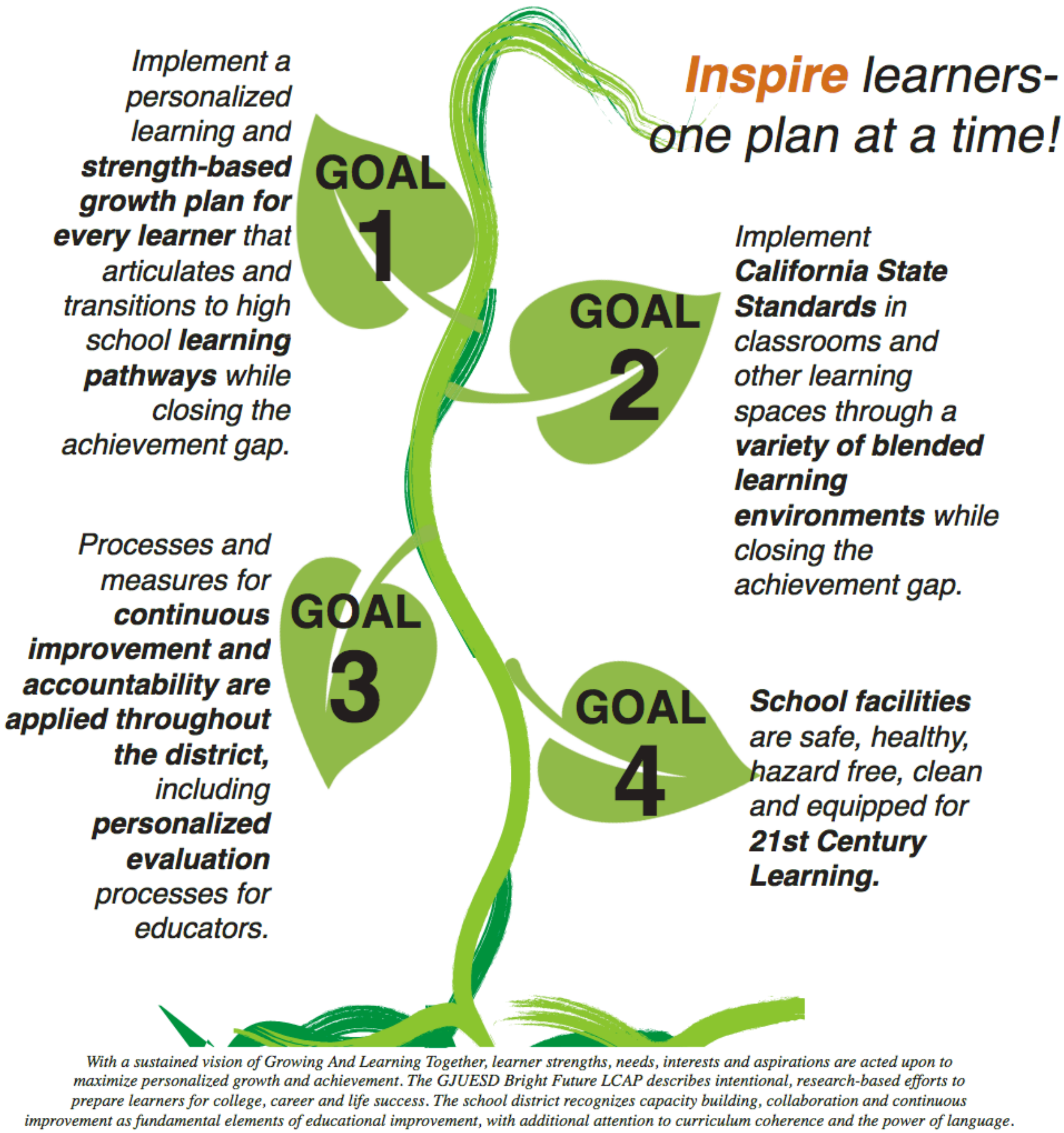
Figure B1. Logic Model for Major Activities and Projected Outcomes for Galt Personalized Learning Initiative



Source: **Galt Joint Union Elementary School District.**

Appendix C: The Galt Growing and Learning Together Model

Figure C1. The Galt Growing and Learning Together Model



Source: Galt Joint Union Elementary School District.

Appendix D: Detailed Description of Data Analysis Procedures Used to Address Research Questions 1 and 2

To address Research Question 1, we regressed the treatment status on post-intervention scores, adjusting for covariates including baseline MAP scores. We used the Benjamini-Hochberg procedure (1995) to adjust for inflation in the Type I error rate in multiple comparisons, due to multiple testing subjects. In addition, we split the sample by SES or ELL status and conducted the subgroup analysis. For individual-level background variables such as SES or ELL status, the reference sample consisted of aggregated matches. It was therefore not feasible to construct meaningful aggregation on such covariates. In other words, the entire reference sample was missing on these background variables, and consequently, the popular missing data treatment that assumes “missing at random” was not applicable.

We considered two solutions: (a) conduct the analysis without such covariates (referred to as Model 0); and (b) interact these variables with the treatment indicator, which was also the missingness indicator (referred to as Model 1). Though we could not assess the degree of imbalance in our samples, the typical test-taking population of MAP was different from the composition of the treatment group. In general, GJUESD has a higher population of disadvantaged and ELL students compared to the national population of students who take MAP assessments. Under Model 0, leaving out the individual-level background variables may not only underpower the study (i.e., make it less likely to detect any meaningful treatment effect), but also may potentially downward-bias the impact estimates (i.e., result in findings of a smaller or more negative effect than the true impact). Model 1, on the other hand, took into account the role of the missing predictors as if they were moderators, since in our study the missing data indicator coincided with the treatment indicator. Therefore, we opted for Model 1, in which the treatment status interacts with the student-level demographic variables. We used this model both to analyze achievement and to examine growth trajectories to explain how the intervention affected students as it took hold over time.

For Research Question 2 on growth trajectories, we also extended the primary model to a mixed effect model, using all waves of spring MAP data as the dependent variable. “Time” was factored into the model in two ways: (a) as a fixed effect that implied growth along the project period, and (b) to interact with the treatment status, which quantified the group difference at each time point. The model also included a random effect at the student level to account for the inter-individual differences. To appropriately account for the intra-personal dependency, we specified the residual to follow a lag-1 autocorrelation, which was allowed to differ across treatment groups. To estimate the model, we used the maximum likelihood estimation method.