Solution Tree's PLC at Work®
in Washoe County School District

Impact Evaluation Report

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Executive Summary

The Solution Tree PLC at Work® intervention aims to bolster student achievement through shifts in adult mindsets, increased collaboration, and student data use to adapt teaching practices to student needs. In school years (SY) 2017-18 and 2018-19, a subset of Washoe County School District schools worked with Solution Tree trainers to implement this model in an effort to improve student outcomes. This study examines student administrative data to describe the impact of the PLC at Work® model to date.

Overall, the PLC initiative appears to be associated with lower disciplinary outcomes, higher attendance, and improved academic outcomes. The positive impact on academic outcomes was particularly pronounced for low-performing students and for students enrolled in schools that have worked with Solution Tree for two years (SY2017-18 and 2018-19). Exhibit 1 displays a summary of findings described in more detail in the body of the report.

Exhibit 1: Summary of Outcomes

	Cohort 1				**Cohort 2**	
	one year of implementation (SY2017-18)		two years of implementation (SY2018-19)		one year of implementation (SY2018-19)	
	All students	Low-performing students	All students	Low-performing students	All students	Low-performing students
Behavior	▲	▲	▼	▲	▲	▲
Attendance	▲▲	▲	▲▲	▲	▲	▲
Math	indet.	▲▲	▲	▲▲	▼▼	▲
ELA	▲	▲	▲	▲▲	▼▼	indet.

Notes: ▲ denotes a substantively important positive effect size (but not statistically significant); ▲▲ denotes a statistically significant positive impact at 95% confidence level; indeterm. denotes an effect that is neither statistically significant nor substantively important; ▼ denotes a substantively important negative effect size; ▼▼ denotes a statistically significant negative impact at 95% confidence level.

However, it is important to note that these findings are preliminary, given the estimated time for this intervention to "take hold" (an estimated 3 years, on average). In addition, given the lack of implementation data in this study, we are unable to measure variation in school implementation and how that may have influenced student outcomes.

Section 1: Introduction

In 2017, Washoe County School District (WCSD) hired Solution Tree, a school transformation professional development provider, to provide training and support to a subset of its lowest-performing schools. Specifically, Solution Tree's training aims to guide schools toward becoming a professional learning community (PLC) through a process called PLC at Work®.

In February 2019, WCSD partnered with Social Policy Research Associates (SPR) to evaluate the effectiveness of the PLC at Work® model at improving student test scores, as well as secondary indicators including attendance and behavior incidents.

About this Report

The analysis in this report primarily draws on student administrative data. We also leveraged additional data sources to inform our understanding of the intervention itself. Data sources used in this evaluation are described in Exhibit 2.

Exhibit 2: Solution Tree Evaluation Data Sources

Source	Description
Administrative data (student records)	SPR collected and analyzed the student records of all WCSD elementary and middle school students between SY2015-16 and 2018-19, including student demographics, standardized assessment scores, discipline, and attendance.
Interviews	We conducted five semi-structured interviews with five of the six Solution Tree trainers working with WCSD schools.
Implementation documents and other literature	We reviewed Solution Tree training materials including participant packets given to WCSD school leaders and books published by Solution Tree on the PLC at Work® model. SPR also conducted a literature review on impact studies of similar interventions to understand the expected timeline for interventions of this nature and methodological approaches.

This report is comprised of four sections. The remainder of Section 1 describes Solution Tree's PLC at Work® model and provides a high-level summary of the implementation of Solution Tree in WCSD. Section 2 describes the research design and methodology for the impact study. Section 3 details the analytical results and main findings, including both overall and subgroup analyses. Finally, the report closes in Section 4 with limitations and considerations.

Solution Tree's PLC at Work®

The architects of Solution Tree's PLC at Work® model define a professional learning community as "an ongoing process in which educators work collaboratively in recurring cycles of collective inquiry and action research to achieve better results for the students they serve."[1] To transform a school into a PLC requires a transformation in adult mindsets and capabilities, and the structures to facilitate continuous improvement.

First and foremost, Solution Tree's goal is to facilitate a **shift in adult mindsets** regarding student potential—that all students can learn at high levels, and that their mission is to ensure that this occurs. Secondly, Solution Tree works with adults to assume **collective responsibility for all students** – shifting from a focus on "my students" to "our students" – to recognize that individual teachers cannot meet the needs of their students alone. Lastly, PLC schools focus on **using student data to adapt and improve their practice** (as opposed to simply collecting it), which is the vehicle for shifts in student outcomes.

To work toward these goals, Solution Tree coaches, who are typically former leaders of successful turnaround schools, help organize its PLC at Work® schools into teams which hold regular structured meetings. These meetings are organized around the following four questions:[2]

1. *What do students need to know and be able to do?* PLC teams agree on what standards their students should know at the end of the school year.
2. *How will we know when they have learned it?* Next, PLC teams create and implement common assessments for each standard and analyze that data together.
3. *What will we do when they haven't learned it?* If the data show that some students haven't mastered a standard, PLC teams create a plan for how to intervene and extend lessons for those students.
4. *What will we do when they already know it?* For students who have already mastered the core content, PLC teams create a plan for enrichment to extend their learning.

While simple and straightforward, these critical questions were designed to ensure that all students achieve an agreed-upon minimum standard of learning. This approach represents a shift from the traditional focus on what is *taught,* to a focus on what is *learned.* Rather than aiming to "cover" academic content, PLC schools work to ensure that every student master all of their grade-level standards. Solution Tree coaches work with school leaders and staff to meet them where they are—as every school begins at a different starting place—and work toward becoming a PLC school. Given the variety in starting places for schools that work with Solution Tree, the expected timeline to achieving this schoolwide shift can vary.

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[1] DuFour, R., DuFour, R., Eaker, R., Many, T. W., & Mattos, M. (2016).

[2] ibid

Solution Tree Implementation in Washoe County School District

WCSD contracted with Solution Tree to provide coaching and support to 12 of the district's highest need schools. Solution Tree coaches began working with six of the schools in the fall of 2017 ("Cohort 1" schools) and with an additional six schools in the fall 2018 ("Cohort 2" schools). The intervention provided to these schools includes two full-day, in-person trainings and five to six full-day, on-site coaching sessions per year.[3] During the initial trainings, Solution Tree coaches met with the principal, teacher leaders, and other staff as appropriate, described what PLCs are and why they work, and facilitated a needs assessment with school leadership. This initial training provided an opportunity to address school-wide cultural issues that may prevent collaborative work within the PLCs. When the Solution Tree coaches return for their on-site coaching sessions, they help school leadership identify what adults at the school have done differently since the initial training, how those changes have impacted students, and what they need to do to push the work forward. Depending on the needs of the school and the guidance of the principal, coaches often met individually with the school's PLC teams during coaching visits. These meetings typically focused on how the teams were using data to increase student learning.

During interviews, the Solution Tree coaches working with Washoe County schools frequently emphasized how school context influenced the implementation of the Solution Tree model in Washoe County. Coaches observed the most progress at schools where the administrators were open to the model and the teachers believed they had the power to help students learn. Within the first year of the intervention at these schools, the PLCs were using student data in different ways, collaboratively deciding how to change their instruction based on the data, and working together to assess how their actions influenced student learning.

When asked about the expected timeline for this work to result in changes at the student level, coaches explained that there can be significant variation based on school starting points. Coaches believed that at the schools who embraced this model and implemented it with fidelity, student assessments could show growth within one year and would likely show growth within three years as the teachers refined these practices. In contrast, coaches reported that other schools were facing various barriers to adopting the model, including resistance or apathy among administrators, weak principal leadership, tension among school staff, and a persistent disbelief among teachers that they could influence student learning. At these schools, Solution Tree coaches continued to build trust, work with staff on improving school climate, and try to shift their perspective on their own efficacy in the classroom. In these cases, the coaches

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[3] For Cohort 2, there was an additional in-person training day for principals only.

believe one to two years is most likely not enough time for changes in adult practices to result in measurable changes in student learning.

Section 2: Research Design

SPR designed an evaluation of Solution Tree's PLC at Work® intervention that aimed to answer the research question:

> "Has the intervention contributed to an increase in student-level academic learning and attendance, and improved disciplinary outcomes?"[4]

To answer this question, we employed a quasi-experimental design (QED) to compare outcomes for students in schools receiving the intervention to those of a comparison group of similar students in schools that did not receive the intervention. The strongest design for the evaluation would have been based on the random assignment of schools to receive the treatment, which would have made the treatment and control groups statistically comparable in all possible characteristics. However, random assignment was not desirable for this study, as the intervention is intended to help Washoe County's lowest-performing schools. Thus, SPR selected a strong QED design for the evaluation which had the potential to meet the second-highest tier of evidence defined by What Works! Clearinghouse (WWC), "Meets WWC Group Design Standards with Reservations."[5]

The analysis was conducted at the student level, because although the intervention was implemented at the school level, the outcomes—an increase in student achievement and attendance, and a decrease in disciplinary events—were ultimately intended to occur at the individual student level.[6]

The QED design estimated the impact of the PLC intervention by comparing the outcomes of "treated" students (that is, students enrolled in schools that participated in the PLC intervention) with an estimate of what would have occurred had the PLC intervention not taken place (otherwise known as the counterfactual). This estimate was calculated by using a comparison group of students who were not affected by the initiative. Because the PLC intervention is a whole-school initiative, all students from PLC schools were affected by it; therefore, it was not possible to identify comparable students from the same school. As a result, we selected a comparison group of students from non-participating schools that were similar to PLC schools. The comparison group selection was done in two steps. First, we selected comparison *schools* that were very similar to PLC schools to account for school-level

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4 Specifically, the outcomes of interest for this study will be: (1) assessment outcomes as measured by the Smarter Balance Assessment, (2) student attendance rates, and (3) number of behavior incidences, suspensions, and expulsions.

5 Lesnick, J., Seftor, N., & Knab, J. (2015).

6 An alternative approach would be to conduct the analysis at the entire school level. The low number of implementing schools, however, makes this option infeasible.

differences that may affect student outcomes. In the second step, we selected *students* within the comparison schools that were very similar to students from PLC schools using a propensity score adjustment design, which is designed to control for any measurable differences between the treatment and comparison groups. The result was two groups of students who were similar in their demographics, pre-intervention outcomes, and the types of schools they attended; the only difference was that one group had attended a PLC school, and the other had not.

Data and Measures

WCSD provided access to student-level data for all elementary and middle school students for SY2015-2016 through 2018-2019. The student-level dataset contained the following types of data fields:

- Grade level
- School attended
- Number of days enrolled
- Demographic information (gender, race/ethnicity, free and reduced lunch status (FRPL), individualized education plan (IEP) designation, and English Learner status)
- Smarter Balanced Assessment (SBA) scores for English language arts (ELA) and mathematics
- Major and minor behavior incidents, suspensions, and absences

Based on this dataset, SPR generated aggregate school-level datasets that, for each school, contained the following:

- Student enrollment
- Proportion of students by racial/ethnic category and gender
- Proportion of students eligible for FRPL
- Proportion of students designated as having an IEP or as English Learners
- Average SBA scores
- Average number of days enrolled, major and minor behavior incidents, suspensions, and absences

The study measured outcomes for students after each year of implementation at their school; for Cohort 1 students at one and two years after implementation began (SY2017-18 and 2018-19, respectively) and Cohort 2 students after one year (SY2018-19). The study analysis included only students with baseline data, i.e., data recorded in the academic year prior to the PLC intervention.[7] Exhibit 3 outlines who was included in the analysis of the outcome areas of interest for each cohort, and the discussion that follows explains why certain students were not included.

[7] For Cohort 1, the baseline year was SY2016-17, and for Cohort 2, the baseline year was SY2017-18.

Exhibit 3: Students Included in Analyses

	Baseline year	K	1	2	3	4	5	6	7	8
Cohort 1 analysis	SY2016-17									
Cohort 2 analysis	SY2017-18									

Notes: = attendance and behavior outcomes; = academic outcomes

Icons in grey were included in one-year follow-up but not two-year follow-up

Students excluded in analyses were:

- **Students in grades K-2 or 8 during their baseline year were not included in academic analysis.** Students in grades K-2 are not assessed using the SBA, as the SBA is vertically aligned only for grades 3 to 8 in ELA and math.[8] We also did not include students who were in grade 8 during the baseline year for the one-year follow-up and grades 7-8 for the two-year follow-up, because these students entered high school once their school began implementing PLC at Work®.
- **Students in grades K or 8 during their baseline year were not included in attendance and behavior analysis.** Students who entered kindergarten during the implementation phase lacked baseline data on behavior and attendance. We also excluded students in grade 8 (and 7-8 for Cohort 1's two-year follow-up) during the baseline year for the same reason mentioned above.

We further removed students who could "contaminate" the sample by transferring between treatment and comparison schools, and students who attended their school of record for less than half the year (discussed more below).

Comparison Group Design

As mentioned earlier, the analysis began by building a comparison group of students who resembled the students affected by the intervention as closely as possible. To achieve this, we selected matches at both the school- and student-level. Because PLC at Work® is a school-wide strategy, and because the selection of PLC schools was done based on performance criteria, we first selected a list of schools that most resembled PLC schools. To do this, we estimated a logistic regression (Equation (1)) on the school-level dataset that estimated the probability of inclusion in the PLC group:

$$logit(T_j) = \beta_0 + \beta_1 X_j + \mu_j \quad (1)$$

8 Smarter Balanced Assessment Consortium (2019).

where T_j represents the treatment assignment for school *j* and is equal to 1 if the school was a PLC school; X_j is a vector of school baseline characteristics, which include demographic characteristics and academic performance indicators averaged for two years before the beginning of the PLC intervention (for Cohort 1 schools) and three years before the beginning of the intervention (for Cohort 2 schools); and μ_j is a school-level error term that captures unobserved variation across schools.

Propensities (i.e. predicted probabilities) derived from the model were used to match PLC and non-PLC schools. For each PLC school, three non-PLC schools with the closest propensities of inclusion were selected; thus, up to 18 comparison schools could be selected for each treatment cohort. However, because several non-PLC schools were selected as comparisons schools for more than one PLC school, the actual number of comparison schools varied between 15 (for Cohort 1) and 12 (for Cohort 2).

Once the comparison schools were selected, student-level analytic samples were created using the criteria identified above in Exhibit 3. In addition, to avoid contamination (a situation when a participant in the comparison group receives the treatment, thus potentially biasing the results), we limited the study sample to only students who were enrolled in either treatment schools or comparison schools during both the baseline and the follow-up year (in other words, we excluded students who were enrolled in a treatment school in one year and a comparison school in the other year). Finally, we excluded students who had been enrolled with their school of record for less than 50 percent of the academic year. This was done to avoid "counting" students' outcomes who did not actually attend their PLC or comparison school for a substantial amount of time.

Section 3: Analysis & Findings

After the final analytic samples were created, we used `teffects ipw`, a Stata procedure that estimates treatment effects from observational data using inverse propensity-score weighting (IPW). This procedure weights regression estimates from the comparison group, such that their weighted means look like the means from the treatment group. In other words, comparison students with a higher probability for treatment are given more weight. The weights are the inverse of estimated treatment probabilities, known as propensity scores (derived using a logistic regression model like the one presented in Equation (1)).

Impacts were calculated as the average treatment effect (ATE), which is the standard treatment effect calculated for this type of intervention.[9]

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[9] The Average Treatment Effect (ATE) is calculated in cases where external application is expected; in other words, it allows one to understand the effect on a broader group of students, not just those who attended a PLC at Work School in Washoe County in SY2017-18 and 2018-19. This is in contrast to Average Treatment Effect on the Treated (ATT), which would isolate the effects on the students who attended PLC school but does not estimate what the effect would have been for comparison students had they attended a PLC school.

Average treatment effects were measured in two ways: first, as an average difference between the treatment group mean and the comparison group mean; and second, an effect size. Following the What Works Clearinghouse guidelines, we calculated effect sizes for continuous variables using the Hedges g measure.[10] Because students are nested into schools, all treatment effects were calculated using clustered robust standard errors,[11] which take into account the nested structure of the data.

Descriptive Analyses

Before the matching procedure took place, we compared the characteristics of students at PLC schools versus non-PLC schools in the year that preceded the PLC intervention (baseline year). As shown in Exhibit 4 below, during the 2016-2017 school year (the baseline year for Cohort 1), students from Cohort 1 PLC schools were much more likely to be eligible for free or reduced-price lunch, were more likely to have limited English proficiency, and had much lower average standardized math and ELA scores than students enrolled in other schools in the district. However, there were very small differences in the average number of minor behavior incidents, suspensions, and attendance rates, and virtually no differences in the percentage of students who had an individualized education plan.

Exhibit 4: Cohort 1 Students Compared to Non-PLC Students at Baseline (SY2016-2017)

	Students enrolled in Cohort 1 schools (n= 3,387)	**Students enrolled in other schools** (n=43,181)
Average minor behavior incidents per student	0.5	0.8
Average suspensions per student	0.1	0.1
Average attendance rate[12] per student	94.4	94.3
Percentage of students eligible for free/reduced-price lunch	71.0%	53.3%
Percentage of students with individualized education plan	13.7%	13.7%

10 Hedges g is a standardized measure of difference that divides the treatment effect by its pooled standard deviation. In Stata, this was implemented by calculating potential outcomes from each estimation and then using the mean and standard deviation of the potential means to calculate Hedges g using the Stata command `esizei`.

11 Clustered robust standard errors are calculated in a way that takes into account that students in the same cluster (here, schools) tend to be more alike than students from other schools. If this assumption holds, clustered standard errors are less biased than regular standard errors (which tend to be artificially small).

12 Defined as the percentage of days attended out of the number of days enrolled at a school in a particular school year.

Percentage of students who have limited English proficiency	21.6%	17.9%
Average SBAC math score	2467	2493
Average SBAC English language arts score	2473	2502

Source: Washoe County School District (2019)

Similarly, Exhibit 5 describes the characteristics of Cohort 2 students compared to students enrolled in non-PLC schools in WCSD during their baseline year. Whereas students enrolled in Cohort 2 schools were in many ways similar to Cohort 1 students, one major difference is that for both math and ELA, the average assessment scores of students in Cohort 2 are much higher and, in the case of ELA, almost identical to that of students enrolled in non-PLC schools. This suggests that the selection of Cohort 1 schools may have succeeded in targeting the schools with the lowest academic outcomes. While Cohort 2 students faced many of the same barriers to learning as Cohort 2 students, their assessment scores did not differ markedly from the rest of the district.

Exhibit 5: Cohort 2 Students Compared to Non-PLC Students at Baseline (SY2017-2018)

	Students enrolled in Cohort 2 schools (n=3,668)	**Students enrolled in other schools** (n=42,750)
Average minor behavior incidents per student	0.6	0.8
Average suspensions per student	0.1	0.1
Average attendance rate per student	94.1	94.0
Percentage of students eligible for free/reduced-price lunch	70.1%	50.0%
Percentage of students with individualized education plan	13.5%	14.3%
Percentage of students who have limited English proficiency	27.1%	17.2%
Average SBAC math score	2,490	2,498
Average SBAC English language arts score	2,499	2,501

Source: Washoe County School District (2019)

Main Impact Findings

We begin by presenting impact findings for Cohort 1. Because the PLC approach was first implemented in SY2017-2018, we can examine impacts at the end of the first implementation year, and then again at the end of the second implementation year. For each outcome, we estimated its mean for the treatment group and for the comparison group; the difference between these means is the estimated average treatment effect. In a separate column, we show the effect size (Hedges g), which is a standardized measure of the ATE that is expressed in standard deviations and is, as a result, comparable across outcomes and can be used to determine whether the finding is large enough to be considered substantively important.[13]

Exhibit 6 below shows impacts for Cohort 1 at the end of the first year after the implementation of PLC. The results from this analysis suggest that the PLC at Work® intervention was associated with a substantively important positive finding in minor behavior accidents[14] (decreased), the attendance rate (increased), and ELA scores (increased), although, only one impact estimate (attendance) was statistically significant after one year of implementation. The impact on math scores was neither statistically significant nor substantively important. Based on this evidence, it appears that the PLC at Work® intervention has a detectable positive effect on attendance, and promising results for behavior and ELA scores.

Exhibit 6: Impact of PLC on Cohort One Student Outcomes (SY2017-2018)

	Treatment group (average)	Comparison group (average)	ATE	Effect size
Number of minor behavior incidents	0.79	0.86	-0.08	**-0.35¥**
Attendance rate	94.6	94.1	**0.6***	**3.01¥**
Standardized math score	2505.3	2506.6	-1.32	-0.12
Standardized ELA score	2516.5	2512.7	3.85	**0.32¥**

Source: Washoe County School District (2019)

*Notes: * denotes statistically significant impact at 95% confidence level using clustered robust standard errors; ¥ denotes substantively important effect size (Hedges g greater than 0.25).*

The results of this analysis after two years of implementation for Cohort 1 are displayed in Exhibit 7. At the end of the second year, the impact of the initiative on attendance was virtually

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13 We use What Works Clearinghouse's threshold of 0.25 standard deviations to denote an impact as "substantively important".

14 Among the three behavior measures available in the dataset, we selected "minor behavior incidents" to include in the impact analysis because (1) major behavior incidents can mean either a single major incident or multiple minor incidents, so for minor incidents, we have a clearer idea of what this means, and (2) suspensions had a very skewed distribution which resulted in very poor balance on covariates.

identical, although it was no longer found to be statistically significant.[15] However, all other estimated impacts—behavior incidents (decrease), math scores (increase), and ELA scores (increase)—were much larger than the 1-year impact estimates, suggesting that the positive effect of the intervention is cumulative for these outcomes, although the lack of statistical significance makes the estimates too imprecise to claim causality.

Exhibit 7: Impact of PLC on Cohort One Student Outcomes (SY2018-2019)

	Treatment group	Comparison group	ATE	Effect size
Number of minor behavior incidents	0.58	0.72	-0.14	**-0.95¥**
Attendance rate	94.9	94.4	0.6	**3.61¥**
Standardized math score	2511.0	2500.8	10.28	**1.66¥**
Standardized ELA score	2523.0	2516.9	6.15	**0.84¥**

Source: Washoe County School District (2019)

*Notes: * denotes statistically significant impact at 95% confidence level using clustered robust standard errors; ¥ denotes substantively important effect size (Hedges g greater than 0.25).*

Next, we examine the impact of the PLC intervention on Cohort 2 students. For Cohort 2, impact estimates (presented in Exhibit 8) suggest that the intervention was associated with lower numbers of minor behavior incidents and higher attendance rates, although the estimates were not statistically significant. More surprisingly, the PLC appeared to be associated with lower academic test scores (both math and ELA) that were both statistically significant and substantively important.

Exhibit 8: Impact of PLC on Cohort Two Student Outcomes (SY2018-2019)

	Treatment group	Comparison group	ATE	Effect size
Number of minor behavior incidents	0.88	1.07	-0.19	**-0.65¥**
Attendance rate	94.4	94.3	0.1	**0.52¥**
Standardized math score	2493.9	2500.8	**-6.94***	**-0.60¥**
Standardized ELA score	2511.8	2518.0	**-6.20***	**-0.50¥**

Source: Washoe County School District (2019)

*Notes: * denotes statistically significant impact at 95% confidence level using clustered robust standard errors; ¥ denotes substantively important effect size (Hedges g greater than 0.25).*

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15 This could occur because of lower sample size. The two-year follow-up analysis for Cohort 1 is based on a smaller sample as students who were enrolled in 7th grade during the baseline year were not included in the analysis.

These results are difficult to interpret without more information about the PLC intervention was executed. However, as seen in Exhibit 5 above, Cohort 2 students were much more similar to non-PLC students in terms of average test scores. In turn, this raises the possibility that the intervention may not have had an impact on all students; it is possible that it may have affected only the students who tend to fall on the lower scale of achievement. To test this hypothesis, we conducted some subgroup analyses, described in the next section.

Subgroup Analyses

For the subgroup analyses, we selected students (both from the treatment and comparison groups) who were underperforming academically or had recorded disciplinary or attendance issues during the baseline year. Thus, we selected students who had the worst outcomes in their baseline year: students with at least one minor behavior accident, students who had less than 94 percent attendance rate, and students who received the lowest math and ELA test scores. We then reran all impact analyses for these groups alone.

The results of subgroup impact analyses are shown in Exhibit 9. For brevity, we only show average treatment effects. The subgroup impact findings appear to support the hypothesis that **the PLC initiative worked especially well for students who were struggling**. This appears particularly true for Cohort 1 students. These students saw large increases in academic achievement, both at the one-year and two-year mark (most of which were also statistically significant) and increases in attendance in both years (also statistically significant). For Cohort 2, the impact on disciplinary outcomes remain unchanged compared to those recorded for all students. However, the impact on the standardized math scores changed its sign (becoming positive) and was substantively important, whereas the impacts on ELA scores became both statistically insignificant and substantively unimportant (and remained negative). Therefore, although struggling students from Cohort 2 did not appear to benefit academically from the initiative quite in the same way, subgroup impacts were still an improvement over those in the general student population.

The fact that subgroup academic impacts were different for the two cohorts suggests there might be something different about how the initiative was implemented in the two cohorts that might be related to academic outcomes. In other words, since all subgroup analyses were conducted on low-performing students, we would expect the impact to be similar (even though there are fewer low-performing students in Cohort 2 compared to Cohort 1). However, without an in-depth implementation study, it is difficult to estimate how the implementation of the initiative differed for the two PLC cohorts.

Exhibit 9: Subgroup Impact Analyses

	Cohort 1: one year	Cohort 1: two years	Cohort 2: one year
Number of minor behavior incidents (students with at least one incident)	-0.87¥	-0.52¥	-0.99¥
Attendance rate (bottom third)	1.0*¥	0.8*¥	0.2¥

Standardized math score (bottom third)	**14.78*¥**	**24.25*¥**	**0.97¥**
Standardized ELA score (bottom third)	**9.28¥**	**16.01*¥**	-0.18

Source: Washoe County School District (2019)

*Notes: * denotes statistically significant impact at 95% confidence level using clustered robust standard errors; ¥ denotes substantively important effect size (Hedges g greater than 0.25).*

Section 4: Conclusion

Overall, the PLC initiative appears to be associated with lower disciplinary outcomes, higher attendance, and improved academic outcomes. The positive impact on academic outcomes was particularly pronounced for low-performing students (as measured at baseline) and for students enrolled in Cohort 1 schools.

Limitations

The primary limitation of this study is the limited time available for the intervention to mature prior to assessing its impact. Based on our conversations with Solution Tree trainers and our review of extant research, interventions of this nature typically require three years to yield positive student-level impacts.[16] At most, the schools in this study received Solution Tree services for two partial school years (Cohort 2), while Cohort 1 schools have only worked with their Solutions Tree coach for one partial school year before we analyzed their outcomes data.

Furthermore, the literature describes PLCs as a type of leadership intervention that is embedded in other complex organizational systems and suggests that their implementation follows a sequential process of coordinated improvement in leadership, instruction, and ultimately student achievement.[17][18] Thus, evaluations of this type of intervention consider increased student success as a long-term outcome preceded by improved school and teacher leadership capacities in the short-term and improved instructional quality, school culture, and climate in the medium-term. Therefore, it is possible that the impact of this intervention will improve over time, and that this study was not able to capture the true effect of becoming at PLC school.

As with any observational study, the impact estimates from our quasi-experimental analysis could be biased if relevant baseline characteristics that have a causal connection to outcomes are not controlled for. Our analyses used a robust set of covariates (both at the school and the student level) to control for factors that could be associated with student behavior and outcomes. However, there are likely unmeasured characteristics that influence both likelihood

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16 Saunders, W. M., Goldenberg, C. N., & Gallimore, R. (2009).

17 Blitz, C. L., & Schulman, R. (2016).

18 Daugherty, L., Herman, R., and Unlu, F. (2017).

of treatment and outcomes, and since schools were not randomly assigned to receive the PLC treatment, findings from observational studies such as this one could still be biased.

Another limitation of this study is that because some students lacked data at baseline (those in grades K-2), the impact of the initiative could not be estimated for the entire group of students who were exposed to the PLC initiative.

In addition, our models used clustered robust standard errors to calculate treatment effects. This is recommended in situations, such as this one, where analytical units are nested into groups (i.e., students are nested into schools). However, given the relatively small number of clusters included in the analysis (approximately 20 schools), clustered robust standard errors computed are quite large, **making most estimates statistically insignificant even where true impacts may exist.** Therefore, the estimates presented in this report are conservative.

Lastly, without implementation data, this study is unable to measure whether schools who adopted the PLC at Work® model with high fidelity and buy-in experienced higher gains among students.

Considerations

We conclude this report with considerations for WCSD. In future studies of similar school-wide interventions, we suggest combining the implementation and impact analyses into one evaluation. Incorporating additional interview, observational, and survey data in any impact analysis will make it easier to interpret impact results, and better inform strategic decision making as a result. Combining these efforts would also make it possible to conduct subgroup analysis by levels of implementation – for example, comparing the impact for schools that implemented the intervention with the highest fidelity to the impact on other schools where student-level effects may take longer.

Lastly, due to the short timeline between implementation of the intervention and this research, we recommend following up with additional impact analysis once the intervention has had more time to take hold in the schools to truly assess the impact of working with Solution Tree to adopt the PLC at Work® model.

Appendix: References

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