Evaluation of the Oakland Health Pathways Project

Technical Report

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Qualitative Methods

To understand the implementation of the Oakland Health Pathways Project (OHPP), as well as gather information on students' experiences in health pathways, researchers from SRI International conducted a range of qualitative data collection activities. Interviews served as the primary source of data and were supplemented by meeting notes and document review.

The SRI research team interviewed 16 individuals in spring 2015, seven individuals in winter 2016, 22 individuals in spring 2016, 16 individuals in fall 2016, 26 individuals in spring 2017, and 37 individuals in spring 2018. At key partnership organizations and programs, these interviewees were executive directors and program managers and, within OUSD, included a Linked Learning director, dual enrollment coordinator, work-based learning coordinators, career and technical education specialist, director of alternative education, and economic development coordinator. At health pathway schools, the SRI team interviewed school administrators; pathway directors, coaches, and teachers; and work-based learning liaisons. The SRI research team also conducted two focus groups with grade 12 health pathway students in spring 2017 and three student focus groups in 2018. SRI researchers attended select meetings and regularly reviewed notes and agendas from other standing meetings to stay abreast of the partnership developments. Over the course of the evaluation, SRI staff interviewed staff from six health pathways, three existing pathways, and three developing pathways.

Exhibit 1. Interviews by Respondent Type

Interview Type	Number of Interviews
District staff	29
Pathway or school staff	55
Partner staff	28
Other	5
Student focus group	5 (groups)

Researchers completed a structured debriefing guide aligned with the study's research questions. After the period in which interviews were conducted, the research team assembled to compare, contrast, and synthesize findings within and across pathways and organizations; to identify overarching themes and initial hypotheses; to determine how these findings related to the quantitative data; and to refine analyses and findings.

Survey Methods

Procedure

To learn about students' experiences of the OHPP, in spring 2018, SRI researchers surveyed seniors in the three health pathways that pre-dated the initiative; the newly established pathways did not have a senior class in 2017-18. The survey was administered online during class time. After arranging times with school staff, SRI researchers visited the schools to conduct the survey during specific class periods in which health pathway seniors were gathered together for core classes. We went to each classroom only once and did not hold make-up survey administration for absent students, meaning only those who were present in class on the prearranged day were available to be surveyed. SRI staff created the survey using the secure online platform Qualtrics. Students took the survey using school-provided laptops. The survey took approximately 15-20 minutes to complete and was done anonymously, meaning students were not asked to enter their names and their personal information was not associated with their responses. Students accessed the survey via a generic web link and unique passcode. The use of the passcode was to ensure one response per student; passcodes were distributed through a random process and were not linked to student names. We provided teachers with a $50 gift card to thank them for facilitating the process, and students were given a $5 gift card for their participation.

Sample

We surveyed a total of 137 students across the three health pathways, out of 190 enrolled. This was a response rate of 72 percent (Exhibit 2).

Exhibit 2. Survey Response Rates by School and Overall

School	Pathway	Enrollment[a]	Number of Respondents	Response Rate
Life Academy	Health & Bioscience Academy	68	41	60%
Oakland High School	Public Health Academy	50	38	76%
Oakland Technical High School	Health Academy	72	58	81%
	Total	**190**	**137**	**72%**

a Source: Schmidke, K. (2019). Oakland Unified School District: Pathway Demographics. Retrieved from: https://dashboards.ousd.org/views/PathwayEnrollment_1/PathwayDemographics?%3Aembed=y&%3Adisplay_count=no&%3Arender=false#54

Analysis

We analyzed the survey data using descriptive analyses. This included calculating means and frequencies of each survey item for the entire sample together. We also analyzed data for each school separately so we could share these results with staff at the schools. However, we did not report by-school results publicly since comparing between schools was not a goal of the study.

Outcomes Analysis

Context and Study Limitations

OUSD implemented the OHPP initiative while simultaneously transitioning to wall-to-wall pathways, meaning they were moving toward having all high school students enrolled in a career-themed pathway. As a result, the number of students remaining in traditional high school programs who could serve as a comparison group for the health pathway students was diminishing as the number of students in pathways increased. This reality created two key study limitations. First, the analysis is limited to one early cohort of students attending a subset of health pathways, limiting the generalizability of findings. Second, the analysis is vulnerable to selection bias.

> **Limited cohort.** The class of 2018 was the first cohort that experienced a complete progression (10^{th} through 12^{th} grade) in pathways enhanced by the OHPP initiative. Because of the transition to wall-to-wall pathways, the class of 2018 was also the last cohort for whom there was a sufficient comparison group of students left in traditional high school programs. As a result, these analyses do not include the four pathways that were newly created as part of the OHPP initiative (two of which are in continuation high schools) because they did not serve the class of 2018.
>
> The three pathways included in these analyses pre-dated the OHPP initiative but were enhanced by the additional supports and partnership opportunities afforded by the initiative. This is the same cohort surveyed in our second brief, Student Experiences in Health Pathways. These findings do not generalize to the newly created health pathways.
>
> **Selection bias.** For the class of 2018, pathway enrollment was still voluntary, but students were increasingly encouraged to enroll in a Linked Learning pathway. The students who continued to choose not to enroll were increasingly likely to be different from those who did in observed and unobserved ways. This type of phenomenon is known as selection bias. If students who chose health career pathways were more motivated, engaged, or had more stable home environments than students who remained in traditional high school programs (all unobserved characteristics), we would expect the bias to result in artificially large health career pathway effect sizes.

For this reason, we also examined health pathway students' outcomes in relation to students in other career-themed pathways (e.g., Engineering; Social Justice Reform; Fashion, Arts, and Design). This secondary pathway-to-pathway comparison provides some context to the focal health pathway vs. traditional high school comparison in that it reduces the threat of selection bias resulting from students choosing to enroll in a pathway instead of remaining in a traditional high school program. However, students who chose a health career pathway may still differ in unobserved ways from those who chose a pathway with a different career theme. This analysis also allowed us to consider whether health pathways specifically had effects on student outcomes above and beyond that of pathways generally.

Data Source

The SRI team worked with OUSD data office staff to obtain student-level demographic, standardized test score, course taking, high school completion, and postsecondary enrollment data directly from district databases. Because career-themed pathways begin in the 10th grade in OUSD, we requested 7th through 12th grade data for all students who were enrolled in 10th grade in the 2015–16 school year. These students had an expected graduation date of June 2018 and were the first cohort that could have experienced a complete health pathway progression (10th through 12th grade) under the OHPP. This is the same cohort described in our second brief, *Student Experiences in Health Pathways.* We received a dataset with records for 2,400 students in January 2019.

Analytic Sample

Our sample of health pathway students consisted of 220 10th graders who were enrolled in health pathways at Life Academy, Oakland High School, and Oakland Technical High School (Exhibit 1). Because these three schools are traditional high schools, we restricted the sample from which we drew our traditional high school and other-pathway comparison groups to students in traditional high schools only. We excluded students in alternative or continuation schools to keep the comparison focused on the presence or absence of pathways within traditional schools rather than introduce other programmatic differences that could be attributed to school type. Our traditional high school comparison group consisted of 870 students at eight traditional high schools who were not enrolled in any career-themed pathway, and our other-pathway comparison group consisted of 1,070 students enrolled in 19 different pathways at eight schools (Exhibit 3).

Exhibit 3. 10th Grade Students in Health Pathways, Traditional High School, and Other Pathways in OUSD Traditional High Schools in 2015–16

School Name	Pathway Name	Number of Students
Health Pathways		
Life Academy	Health and Bioscience Academy	71
Oakland High School	Public Health Academy	64
Oakland Technical High School	Health Academy	85
	Total	**220**
Traditional High School		
Coliseum College Preparatory Academy	N/A	3
Castlemont High School	N/A	67
Fremont High School	N/A	17
Madison Park Academy	N/A	109
McClymonds High School	N/A	49
Oakland High School	N/A	82
Oakland Technical High School	N/A	245
Skyline High School	N/A	298
	Total	**870**
Other Pathways		
Coliseum College Preparatory Academy	Community Leadership and Service	34
Coliseum College Preparatory Academy	Entrepreneurship Pathway	33
Castlemont High School	Sustainable Urban Design Academy	83
Fremont High School	College Prep and Architecture Academy	96
Fremont High School	Mandela Law and Public Service Academy	63
Fremont High School	Media Academy	45
McClymonds High School	Project Lead the Way	33
MetWest High School	Social Entrepreneurship Pathway	42
Oakland High School	Khepera Pathway of Social Innovation	21
Oakland High School	Environmental Science Academy	62
Oakland High School	Project Lead the Way	72
Oakland High School	Social Justice Reform	56
Oakland High School	Visual Arts and Academics Magnet	61
Oakland Technical High School	Computer Academy	57
Oakland Technical High School	Engineering Academy	54
Oakland Technical High School	Fashion, Arts, and Design Academy	63
Skyline High School	Computer Science and Technology Academy	65
Skyline High School	Education Academy	68
Skyline High School	Green Academy	62
	Total	**1,070**
	Grand Total	**2,160**

The analytic sample for each outcome of interest varied from these starting numbers based on the number of students for whom we had outcome data and whether other outcome-specific exclusions were made. Key exclusions include:

- Students' whose graduation status[1] on or prior to June 2018 was "removed from cohort," meaning the student left the state or country, transferred to a private school or another California district with a high school diploma program, or died, and was excluded from the analytic sample for all end-of-high-school and postsecondary outcomes. These students remained in the sample for 11th grade high school achievement tests if they had scores, indicating they were still present at the time of the test.
- Students who dropped out of high school were excluded from analyses of the course-related outcomes (i.e., credits earned, a-g status, number of a-g requirements met) because if pathways tend to reduce dropout, then including dropouts (who stop taking courses and are potentially disproportionately present in the traditional high school group) could artificially inflate pathway students' course outcomes. By limiting these outcomes to non-dropouts, the results reflect the additional work students complete during high school and are not the product of students staying in school rather than dropping out.

Covariates

In our analysis of students' high school and postsecondary education outcomes, we controlled for a variety of demographic and prior achievement variables. Exhibit 4 lists the variables we included as covariates in our statistical models, including descriptions of how we created each variable.

[1] OUSD graduation status categories (submitted to and updated from the California Longitudinal Pupil Achievement Data System [CALPADS]) include: removed from cohort; adult graduate; California High School Proficiency Exam (CHSPE) completer; dropout; General Educational Development (GED) completer; graduate; null; special education certificate; still enrolled; and transfer. "Removed from cohort" means the student left the state or country, transferred to a private school or another California district with a high school diploma program, or died. "Transfer" means the student transferred to an adult education program or community college. "Null" means data were missing. See: https://www.cde.ca.gov/ds/sp/cl/gradcohortguidance18att1.asp

Exhibit 4. Student Demographic and Prior Achievement Covariates Used in Analyses

Variable	Description
Student Demographics	
Gender	Equal to 1 if student was female. Equal to 0 if student was male.
Latino	Equal to 1 if student was Latino. Equal to 0 if student was not Latino.
African American	Equal to 1 if student was African American. Equal to 0 if student was not African American.
Asian	Equal to 1 if student was Asian. Equal to 0 if student was not Asian.
White	Equal to 1 if student was White. Equal to 0 if student was not White.
Multiple race/ethnicities	Equal to 1 if student was multi-racial. Equal to 0 if student was not multi-racial.
Other race/ethnicity	Equal to 1 if student was American Indian/Alaska Native, Filipino, or Pacific Islander. These categories were combined due to small sample size, where students could potentially be identified even in aggregate data. Equal to 0 if student was not American Indian/Alaska Native, Filipino, or Pacific Islander.
Gifted and Talented (GATE)	Equal to 1 if student was in gifted and talented program in the 8th grade. Equal to 0 if student was not in gifted and talented program in the 8th grade.
English Language Learner (ELL)	Equal to 1 if student was an English Language Learner in 9th grade. Equal to 0 if student was categorized as English Only, Initial Fluent English Proficient, or Reclassified Fluent English Proficient in the 9th grade.
Special education (SP ED)	Equal to 1 if student had special education status in the 9th grade. Equal to 0 if student did not have special education status in the 9th grade.
Prior Achievement	
ELA CST	7th grade English Language Arts California Standards Test[a] score. Scale scores range from 150–600.
Math CST z-score	Z-score created from 7th grade mathematics CST score and Algebra I CST score.[b] Scale scores for both tests range from 150–600. Z-scores are zero-centered and allow us to take two different tests and use them as a single math score.
9th grade GPA	Grade-point average based on student's 9th grade course work.
9th grade a-g on track	Number of OUSD 9th grade internal course credit targets for the a-g subject areas[c] that were met, on continuous scale of 0–7.

[a]OUSD administered the California Standards Test (CST) for the last time in 2012–13, when our cohort was in the 7th grade. In 2014–15, they began using the Smarter Balanced Assessment Consortium (SBAC) tests. They did not administer a test consistently to all students in 2013–14, which was a transition year, so we rely on 2012–13 CST data to account for students' prior achievement in our analyses.

[b]Students in our cohort took either the grade-level math (*n* = 1,269) or algebra (*n* = 92) CST test in the 7th grade, corresponding to the course they were enrolled in. Although the two tests use the same reporting scale, scores are not exactly comparable so we converted them to z-scores using state-level means and standard deviations reported by the California Department of Education in their spring 2013 CST technical report found here: https://star.cde.ca.gov/techreports/CST/cst13techrpt.pdf. This allowed us to use one single 7th grade math score in our analyses.

[c]The a-g subject areas (based on University of California [UC] and California State University [CSU] college eligibility requirements) are as follows: A – history/social science; B – English; C – math; D – laboratory science; E – language other than English; F – visual and performing arts; G – college preparatory elective.

Outcomes

In addition to the demographic and prior achievement data described above, we also received high school and postsecondary outcome data for our cohort of students. Exhibit 5 lists the outcomes we examined in our statistical models, including descriptions of how we created each variable and determined its analytic sample.

Exhibit 5. High School and Postsecondary Outcome Variables

Variable	Description	Variable Creation and Analytic Sample
High School Achievement Tests		
ELA SBAC	11th grade ELA Smarter Balanced Assessment score. Scale scores range from 2299–2795.[a]	Used records for 11th grade only, regardless of associated school year.[b]
Math SBAC	11th grade Math Smarter Balanced Assessment score. Scale scores range from 2280–2862.	Used records for 11th grade only, regardless of associated school year.
End-of-High-School Outcomes		
Credits earned	Total number of course credits earned in three-year period of 2015–16, 2016–17, and 2017–18 (the expected grade progression), regardless of the actual grade student was in for each year.	Calculated using credits associated with each course taken and passing status,[c] only for students who did not drop out or move out of state/transfer to high school in another district.[d]
a-g status	Equal to 1 if student met all seven a-g requirements for UC/CSU college eligibility as of June 2018. Equal to 0 if student did not meet all seven a-g requirements by June 2018 and the a-g values were nonmissing.	Calculated only for students who were in 12th grade in the 2017–18 year and did not drop out or move out of state/transfer to high school in another district.
Number of a-g requirements met	Number of a-g requirements met as of June 2018, on continuous scale of 0–7.	Calculated only for students who were in 12th grade in the 2017–18 year and did not drop out or move out of state/transfer to high school in another district.
Dropout	Equal to 1 if student graduation status as of or prior to June 2018 was dropout, OR if graduation status was missing but student attendance status in 2017–18 was inactive and student also earned no course credits in 2017–18.[e] Equal to 0 if student graduation status in June 2018 was adult graduate; CHSPE completer; GED completer; graduate; special education certificate; still enrolled; or transfer.	Calculated only for students who had nonmissing graduation status and did not move out of state/transfer to high school in another district.
High school graduation	Equal to 1 if student graduation status as of or prior to June 2018 was graduate (i.e., on-time graduation). Equal to 0 if student graduation status in June 2018 was adult graduate; CHSPE completer; GED completer; graduate; special education certificate; still enrolled; or transfer.[f]	Calculated only for students who had nonmissing graduation status and did not move out of state/transfer to high school in another district.
Postsecondary Outcomes		
College enrollment	Equal to 1 if student enrolled in a 2- or 4-year[g] college in fall 2018. Equal to 0 if student did not enroll in a 2- or 4-year college in fall 2018 but did complete high school in June 2018.	Calculated only for students who completed high school (i.e., graduate or equivalent)[h] in June 2018.
4-year (vs. 2-year) college enrollment	Equal to 1 if student enrolled in a 4-year college in fall 2018. Equal to 0 if student enrolled in a 2-year college in fall 2018.	Calculated only for students who enrolled in college in fall 2018. All other students with no record of college enrollment excluded from analytic sample.

[a]See https://caaspp.cde.ca.gov/sb2018/ScaleScoreRanges.

[b]If students repeated 11th grade and had multiple SBAC records, the record with the highest score was used.

[c]OUSD provided us with “credits attempted,” “credits earned,” and “course grade” data as part of each course record. Credits earned is a precalculated variable that already accounts for whether students received a passing grade (i.e., letter grades A–D, credit, or pass). We used the following rules in cleaning the credits earned data: if a student did not pass the course but still received credits earned, we set the credits earned to 0; if a student passed but was not given credits earned and there was an associated number of credits attempted for the course, we set the credits earned to equal the credits attempted.

[d]Move out of state/transfer to high school in another district = OUSD graduation status “removed from cohort.”

[e]Using these criteria, we recategorized 225 students’ graduation status from null to dropout. We felt that simultaneously having inactive enrollment status and no course credits earned in 2017–18 was a strong indicator a student had dropped out by that year although the district data system had not formally classified the student as a dropout. After recategorization, 36 students remained in the null category.

[f]We defined graduate using the updated 2017 state criteria found here: https://www.cde.ca.gov/nr/ne/yr18/yr18rel50.asp. Students who receive adult education high school diplomas or passed the CHSPE exam are no longer considered regular high school

graduates, along with students who receive GEDs or special education certifications.
[g]If a student's records indicated enrollment in multiple institutions including both 2- and 4-year colleges, we designated the student as a 4-year college enrollee.
[h]This is because OUSD receives postsecondary enrollment data from the National Student Clearinghouse (NSC) for only those students who completed high school within the district. This includes graduates, adult graduates, CHPSE completers, GED completers, and those who received special education certificates. This excludes students whose graduation status was dropout, null, still enrolled, transfer, or removed from cohort.

Sample Descriptive Statistics

To prepare the data for analysis and minimize errors, we used the following data-cleaning steps for all variables where applicable:

- If students were in the same grade for multiple school years (e.g., in 10th grade in 2014–15 and again in 2015–16) but a single school year needed to be selected to represent a particular grade, we deleted records that were not in the target cohort year (i.e., 10th grade in 2015–16) or in the expected grade progression (i.e., 11th grade in 2016–17, 12th grade in 2017–18).
- If students repeated courses, we kept the course record with the highest grade earned and deleted the others.

Exhibit 6 shows the unadjusted means, standard deviations, and sample sizes for the demographic and prior achievement covariates of our three groups: health pathway, traditional high school, and other pathway students. These overall descriptive statistics display how the characteristics of students enrolled in health pathways differ from those of students not enrolled in any pathway, as well as from students enrolled in other career-themed pathways.

Given that demographic characteristics often serve as proxy variables for risk factors such as poverty, and prior achievement is frequently a strong predictor of later achievement, these characteristics suggest that *prior to enrolling in pathways,* health pathway students were a lower risk group that was more likely to achieve academic success compared to students in traditional high school programs. The characteristics of students in other pathways suggest that they are, on average, less advantaged and lower achieving than students in health pathways but more advantaged and higher achieving than traditional high school students.

Exhibit 6. Unadjusted Demographic and Prior Achievement Descriptive Statistics for Health Pathway, Traditional High School, and Other Pathway Groups

Variable	Health Pathway			Traditional High School			Other Pathway		
	Mean	*SD*	*n*	Mean	*SD*	*n*	Mean	*SD*	*n*
Student Demographics									
Female	0.45	0.50	220	0.58	0.49	870	0.51	0.50	1070
Latino	0.44	0.50	218	0.43	0.50	863	0.41	0.49	1060
African American	0.19	0.40	218	0.32	0.47	863	0.31	0.46	1060
Asian	0.18	0.39	218	0.12	0.32	863	0.17	0.38	1060
White	0.12	0.33	218	0.08	0.27	863	0.07	0.25	1060
Multiple race/ ethnicities	0.04	0.19	218	0.02	0.12	863	0.01	0.10	1060
Other race/ethnicity	0.03	0.16	218	0.03	0.17	863	0.04	0.19	1060
GATE	0.22	0.41	212	0.14	0.34	673	0.18	0.38	934
ELL	0.15	0.36	219	0.22	0.41	741	0.19	0.39	1021
SP ED	0.11	219	219	0.15	0.35	749	0.12	0.32	1025
Prior Achievement									
ELA CST	351	58.6	164	334	54.7	460	343	59.2	687
Grade-level math CST	334	61.0	147	322	57.9	441	331	63.6	634
Algebra CST	381	43.0	17	362	57.9	19	379	71.2	56
Math CST z-score	-0.25	0.92	164	-0.49	0.9	460	-0.32	0.97	690
9th grade GPA	2.9	0.89	219	2.30	1.2	706	2.6	1.1	997
9th grade a-g on track	6.4	0.98	219	5.50	1.3	661	6.0	1.2	982

Note. GATE= Gifted and Talented; ELL = English Language Learner; SP ED = special education. We combined Filipino, Native American/Alaska Native, and Pacific Islander into a single “other race/ethnicity” group because sample sizes were less than 5 in each category in the health pathway group.

Exhibit 7 shows the unadjusted means, standard deviations, and sample sizes for the high school and postsecondary outcomes of health pathway, traditional high school, and other pathway students. As with the demographic and prior achievement covariates, the outcomes of students in other pathways were often lower than those of health pathway students but higher than those of traditional high school students.

Exhibit 7. Unadjusted Outcome Descriptive Statistics for Health Pathway, Traditional High School, and Other Pathway Groups

Variable	Health Pathway			Traditional High School			Other Pathway		
	Mean	*SD*	*n*	Mean	*SD*	*n*	Mean	*SD*	*n*
High School Achievement Tests									
ELA SBAC	2579	115	197	2538	121	514	2554	120	811
Math SBAC	2514	120	201	2480	124	502	2503	132	789
End-of-High-School Outcomes									
Credits earned	206	37.3	200	185	43.8	676	207	38.9	916
a-g status	0.69	0.46	190	0.38	0.49	559	0.54	0.50	836
Number a-g req met	6.2	1.4	190	5.2	2	559	5.9	1.6	836
Dropout	0.08	0.28	215	0.22	0.41	846	0.14	0.35	1052
HS graduation	0.88	0.33	215	0.63	0.48	846	0.79	0.40	1052
Postsecondary Outcomes									
College enrollment	0.70	0.46	192	0.56	0.50	579	0.62	0.49	842
4-yr (vs. 2-yr) college enrollment	0.57	0.50	135	0.51	0.50	323	0.59	0.49	520

Analysis Methods

To run the most rigorous analysis possible within the constraints of our study context, we first imputed missing data to preserve sample size and maximize statistical power. We then used propensity score weighting (PSW) to try to statistically equate the health pathway group first with the traditional high school group, and then with the other pathway group. This weighting is especially important in light of the large differences between the health pathway and traditional high school groups in baseline (i.e., pre-intervention) demographic and prior achievement measures. Last, we used Hierarchical Linear Modeling (HLM) to estimate the effect of health pathway participation on student outcomes compared first to traditional high school participation and then to participation in other career-themed pathways.

MISSING DATA IMPUTATION

Among the 2,160 students that we have at least some data for, the missing data rates range from 51 percent to 2 percent for outcome variables and 0 percent to 36 percent for baseline covariates. Complete-case analysis using an unimputed data set has substantial weaknesses when considerable data are missing. First, listwise deletion limits the statistical power of the tests conducted because it uses a reduced sample size with complete cases (Allison, 2001; Olinsky, Chen, & Harlow, 2003; Roth, 1994). Second, if there is systematic difference between the complete cases and incomplete cases, the statistical inference from complete-case analysis may not be applicable to the population of all cases.

We utilized multiple imputation as an alternative technique for dealing with missing data in an attempt to eliminate this bias. We imputed missing data on baseline demographic and prior achievement measures using the EM (expectation-maximization) algorithm. Following What Works Clearinghouse (WWC) standards 4.0, the imputation model for each outcome variable included an indicator variable for treatment condition, all baseline demographic and prior achievement measures, and the outcome variable. We used the SAS PROC MI procedure with EM statement for multiple imputation. Multiple imputation inference involves three distinct phases:

- For each imputation, the missing data are filled in ten times to generate ten complete data sets.
- The ten complete data sets are analyzed by using descriptive and mixed model procedures.
- The mixed-model results from the ten complete data sets are combined for subsequent inferential analyses using SAS PROC MIANALYZE.

In our analyses, we conducted imputation nine times, once for each outcome variable. As an example, for the ELA SBAC outcome, the multiple imputation model included the pathway indicator variable, the ELA SBAC outcome variable, and all of the baseline covariates listed in Exhibit 5 (gender, race/ethnicity, GATE, ELL, special education status, ELA CST, math CST z-score, 9th grade GPA, and 9th grade a-g on track). Multiple imputation filled in the missing data for all baseline characteristics and generated 10 imputed datasets. The outcome variable was used to improve the accuracy of the imputation of baseline variables but was not itself imputed. For each outcome, we restricted our imputed sample to students who had nonmissing outcome data. Again, to improve the accuracy of the imputation, we used the entire original dataset of 2,400 students and drew from the maximum amount of available data although only 2,113 are in our largest analytic sample.

PROPENSITY SCORE WEIGHTING

Propensity score techniques are quasi-experimental approaches developed to approximate findings from randomized controlled trials (Becker & Ichino, 2002). They have been increasingly used in observational studies with cohort designs to reduce selection bias in estimating treatment or intervention effects when randomized controlled trials are not feasible or ethical (Rosenbaum & Rubin, 1983, 1984, 1985).

In our evaluation of the OHPP, it was not feasible to randomly assign students to health pathway or traditional high school programs of study. Instead, students self-selected into different pathway programs. We used propensity score weighting methods to statistically equalize the mean values of potentially confounding covariates (e.g., student baseline demographic characteristics and prior achievement) for the two groups within each of our two comparisons (health pathway vs. traditional high school and health pathway vs. other pathway), ensuring that differences in outcomes were not the result of differences in the covariates. The propensity score is the predicted probability of participating in a health pathway based on a set of potentially confounding covariates. For each outcome variable, we conducted propensity score weighting twice using two separate logistic regression models: once using traditional high school as the reference group and a second time using other pathway as the reference group.

Specifically, to contrast health pathway students with students in traditional high school, we set the weight for pathway students to 1.0 and the weight for traditional high school comparison students to pi/(1-pi), where pi is the propensity score for the i-th comparison student. The weighting created balance between the two groups on observed covariates and thus the estimated effect of health pathway participation on student outcomes is more accurate. We selected weighting over other approaches such as matching because it retains all sample members in the analysis and does not reduce sample size.

After applying propensity score weighting to the comparison students, we examined the standardized mean score difference—d, the difference between treatment and comparison group means divided by a pooled standard deviation—for each covariate to ensure it was less than 0.25, thereby indicating covariate balance (What Works Clearinghouse, 2017). We also calculated the standardized mean score difference, d, without using propensity score weights (also called d before propensity score weighting). Exhibit 7 shows the two sets of ds (d before PSW and d after PSW) for the health pathway vs. traditional high school comparison for the SBAC ELA outcome. Before propensity score weighting, the d on covariates ranged from -0.21 to 0.36 standard deviations whereas after propensity score weighting, the d on covariates ranged from -0.028 to 0.02 standard deviations. This is lower than the What Works Clearinghouse 0.25 standard deviation cutoff for baseline equivalence for quasi-experimental studies in most cases (What Works Clearinghouse, 2017). In other words, health pathway and traditional high school students were very similar on all potentially confounding covariates after propensity score weighting. Similarly, Exhibit 8 (differences between health pathway and other pathway students for SBAC ELA) shows acceptable equivalence on all covariates. Analogous exhibits for the remaining health pathway vs. traditional high school outcomes can be found in Appendix A of the *Student Outcomes in Health Pathways* technical report, and exhibits for the remaining health pathway vs. other pathway outcomes can be found in Appendix B of the same report.

Exhibit 7. Imputed Demographic and Prior Achievement Variables for Health Pathway and Traditional High School Students Before and After Propensity Score Weighting, SBAC ELA Outcome

Variable	Health Pathway (*n* = 197)	Traditional High School (*n* = 514)		Traditional High School (n = 514)	
	Imputed Mean	Imputed Mean	Before PSW d	PS weighted Mean	After PSW d
Female	0.55	0.50	0.11	0.55	0.002
African American	0.18	0.27	-0.21	0.18	-0.010
Asian	0.19	0.20	-0.02	0.20	-0.006
White	0.13	0.08	0.19	0.13	0.001
Multiple race/ethnicities	0.04	0.01	0.23	0.04	-0.028
Other race/ethnicity	0.03	0.04	-0.05	0.03	-0.004
GATE	0.22	0.19	0.07	0.22	-0.012
ELL	0.13	0.17	-0.09	0.13	0.020
SP ED	0.09	0.10	-0.03	0.10	-0.026
ELA CST	350	343	0.11	350	-0.014
Math CST z-score	-0.25	-0.32	0.07	-0.26	0.006
9th grade GPA	3.0	2.8	0.21	3.0	0.010
9th grade a-g on track	6.5	6.1	0.36	6.5	-0.001

Note. GATE= Gifted and Talented; ELL = English Language Learner; SP ED = special education. Male served as the reference group for the gender variables and Latino was the reference group among race/ethnicity variables.

Exhibit 8. Imputed Demographic and Prior Achievement Variables for Health Pathway and Other Pathway Students Before and After Propensity Score Weighting, SBAC ELA Outcome

Variable	Health Pathway (*n* = 197)	Other Pathway (*n* = 811)		Other Pathway (*n* = 811)	
	Imputed Mean	Imputed Mean	Before PSW d	PS weighted Mean	After PSW d
Female	0.55	0.50	0.11	0.55	0.002
African American	0.18	0.27	-0.21	0.18	-0.010
Asian	0.19	0.20	-0.02	0.20	-0.006
White	0.13	0.08	0.19	0.13	0.001
Multiple race/ ethnicities	0.04	0.01	0.23	0.04	-0.028
Other race/ethnicity	0.03	0.04	-0.05	0.03	-0.004
GATE	0.22	0.19	0.07	0.22	-0.012
ELL	0.13	0.17	-0.09	0.13	0.020
SP ED	0.09	0.10	-0.03	0.10	-0.026
ELA CST	350	343	0.11	350	-0.014
Math CST z-score	-0.25	-0.32	0.07	-0.26	0.006
9th grade GPA	3.0	2.8	0.21	3.0	0.010
9th grade a-g on track	6.5	6.1	0.36	6.5	-0.001

Note. GATE= Gifted and Talented; ELL = English Language Learner; SP ED = special education. Male served as the reference group for the gender variables and Latino was the reference group among race/ethnicity variables.

HIERARCHICAL LINEAR MODELS

We used HLM to test the difference in outcomes between health pathway and traditional high school students, as well as between health pathway and other-pathway students, adjusting for confounds using inverse propensity score estimators, as recommended by Rosenbaum and Rubin (1983). The coefficient associated with health pathway membership can be interpreted as the measure of the difference in student outcomes between health pathway and comparison groups, adjusting for the estimated propensity of being in the health pathway group as well as baseline demographics and prior achievement.

We performed a set of two-level HLMs to account for the nesting structure of the data ─ students were nested within schools. We conducted our analyses using SAS 9.0 PROC MIXED and PROC GLIMMIX commands. The high school and postsecondary outcomes described in Exhibit 5 were the dependent variables. A constant, a pathway indicator variable, baseline student demographics, and prior achievement scores were the independent variables.

Outcome *Y* for student *i* in School *j* is given as

$$Y_{ij} = \gamma_{00} + \gamma_{01} Pathway_{ij} + \gamma_{02} P_{ij} + \gamma_{03} D_{ij} + \mu_{0j} + e_{ij}$$

where:

$Pathway_{ij}$ = 1 for students in the health pathway and 0 for students in comparison group.

P_{ij} = student prior achievement scores, including 7th grade ELA and math CST, 9th grade GPA, and 9th grade a-g on track.

D_{ij} = student demographic characteristics, including gender, race/ethnicity, GATE status, ELL status, and special education status.

μ_{0j} = school random effect.

e_{ij} = student random effect.

The coefficient γ_{01} associated with $Pathway_j$ in the above HLM indicates the average treatment effect in promoting improved student outcomes. All the covariates were grand-mean centered; therefore, our estimates predicted differences for an "average" student in the sample. We use the standard *p* < .05 threshold to determine statistical significance throughout this report. To indicate the magnitude of the difference between health pathway and comparison groups, we report Hedges' g effect sizes for continuous outcomes. We calculated effect sizes by dividing the coefficient associated with the intervention effect from the HLM by the pooled within-group standard deviation of the outcome at the student level (What Works Clearinghouse, 2017).

For categorical outcomes, we report Cox index effect sizes, which are calculated by dividing the logged odds ratio by 1.65 (What Works Clearinghouse, 2017). For ease of interpretation in the brief, we also report percentage point differences in predicted probability for categorical outcomes. We calculated this by determining each student's predicted probability individually, calculating the mean of the individual probabilities for treatment and comparison groups, and then subtracting the comparison group's mean probability from the treatment group's mean probability to result in a percentage point difference.

Results

We found health pathway students significantly outperformed traditional high school students in high school course credits earned, number of college eligibility requirements met, graduation, and college enrollment (Exhibit 9).[2] The two groups did not differ in high school English Language Arts and math achievement, completion of college eligibility requirements, drop out,[3] and enrollment in 4-year (rather than 2-year) college.

In interpreting these results, it is important to remember they are for a single cohort of students. Also, because the OUSD was moving to a wall-to-wall pathway implementation, the pool of students in the traditional high school comparison group was shrinking (and becoming less "traditional"), so our results may be affected by selection bias that inflates the effects of health pathways. We used statistical methods to correct for *measured* differences between the health pathway and traditional high school students but are unable to account for selection bias based on unobserved characteristics (e.g., motivation, engagement, stability of home environment).

For full HLM results comparing students in health pathways with students in traditional high school programs, see Appendix C of the *Student Outcomes in Health Pathways* technical report.

[2] We explored using coarsened exact matching (CEM) as an alternative to propensity score weighting (PSW) for constructing our comparison group to test whether a different approach would give different results. Using CEM on the college enrollment outcome gave a treatment estimate very similar to the treatment estimate derived using PSW, with health pathway students more likely to enroll in college than traditional high school students. However, the difference in groups did not reach statistical significance. This was likely due to the dramatic reduction in sample size and associated increase in standard error that occurred when using CEM, which relies on matching treatment students with similar comparison students (rather than weighting comparison students to increase their similarity to treatment students). However, the comparability in treatment estimates indicates that CEM created matched samples very similar to the weighted groups created using PSW—so theoretically, if samples sizes were larger, the CEM model would likely have reached statistical significance with results similar to PSW. This indicates the two approaches give similar results, so we can view our findings using PSW with more confidence.

[3] We altered students' graduation status by recoding from missing to dropout if their attendance status was inactive during the 2017–18 year and they also accumulated no course credits during the 2017–18 year. Therefore, we examined whether using the original dropout data with no recoding resulted in different findings. It did not; there was no difference in likelihood of dropout between health pathways and traditional high school students regardless of which dropout variable (original or recoded) we used.

Exhibit 9. Propensity Score Weighted Treatment Estimates for High School and Postsecondary Outcomes, Comparing Health Pathway with Traditional High School Students

Variables	Coeff	*SE*	G_1 Est	G_2 Est	% Pt Diff	*P*	Effect Size	n_{s1}	n_{s2}	n_{t1}	n_{t2}
ELA SBAC	-1.63	6.7	2539	2540		0.81	-0.01	3	8	197	514
Math SBAC	-2.29	8.9	2477	2479		0.80	-0.02	3	8	201	502
Credits earned	7.8**	2.9	193	185		0.007	0.18	3	8	200	676
a-g status	0.43	0.4	0.46	0.42	4	0.29	0.29	3	8	190	559
Number a-g requirements met	0.21*	0.1	5.3	5.1		0.04	0.11	3	8	190	559
Dropout	-0.26	0.4	0.21	0.24	-3	0.54	0.23	3	8	215	846
HS graduation	0.78*	0.3	0.70	0.59	11	0.02	0.27	3	8	215	846
College enrollment	1.07**	0.4	0.66	0.46	20	0.008	0.30	3	8	192	579
4-yr (vs. 2-yr) college enrollment	-0.72	0.4	0.39	0.50	-11	0.09	0.30	3	8	135	323

Note. G_1 Est = model-adjusted mean outcome for health pathway group; G_2 Est = model-adjusted mean for traditional high school group; n_{t1} = number of health pathway students included in the HLM analysis; n_{t2} = number of traditional high school students included in the HLM analysis. n_{s1} = number of schools that have health pathway students in the HLM analysis; n_{s2} = number of schools that have traditional high school students in the HLM analysis. Two schools have both health pathway and traditional high school students.

The HLM results reported here are based on two-level models (students nested in schools). Students' baseline demographic characteristics and prior achievement scores were imputed if there were any missing. Students' outcome data were not imputed. The HLM controlled for student demographic characteristics and prior achievement scores.

Effect sizes for continous outcomes are reported using Hedge's g. Effect sizes for categorical outcomes are reported using Cox's index.

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

We also found health pathways students did not differ from students in other career-themed pathways on any of these nine outcomes (Exhibit 10). For full HLM results comparing students in health pathways with students in other career-themed pathways, see Appendix D of the *Student Outcomes in Health Pathways* technical report.

Exhibit 10. Propensity Score Weighted Treatment Estimates for High School and Postsecondary Outcomes, Comparing Health Pathway with Other Pathway Students

Variables	Coeff	*SE*	G_1 Est	G_2 Est	% Pt Diff	*p*	Effect Size	n_{s1}	n_{s2}	n_{t1}	n_{t2}
ELA SBAC	2.38	6.33	2556	2553		0.71	0.02	3	8	197	811
Math SBAC	-12.49	7.32	2490	2502		0.09	-0.10	3	8	201	789
Credits earned	1.8	2.3	206	204		0.43	0.04	3	8	200	916
a-g status	-0.09	0.40	0.59	0.60	1	0.83	0.29	3	8	190	836
Number a-g requirements met	0.03	0.08	5.9	5.9		0.67	0.02	3	8	190	836
Dropout	-0.13	0.39	0.13	0.15	-2	0.74	0.23	3	8	215	1052
HS graduation	0.23	0.33	0.80	0.78	2	0.50	0.27	3	8	215	1052
College enrollment	0.49	0.31	0.68	0.59	9	0.12	0.30	3	8	192	842
4-yr (vs. 2-yr) college enrollment	-0.55	0.36	0.54	0.63	-9	0.13	0.30	3	8	135	520

Note. G_1 Est = model-adjusted mean outcome for health pathway group; G_2 Est = model-adjusted mean for other pathway group; n_{t1} = number of health pathway students included in the HLM analysis; n_{t2} = number of other pathways students included in the HLM analysis. n_{s1} = number of schools that have health pathway students included in the HLM analysis; n_{s2} = number of schools that have other pathways students in the HLM analysis. Two schools have both health pathway and other pathway students.
The HLM results reported here are based on two-level models (students nested in schools). Students' baseline demographic characteristics and prior achievement scores were imputed if there were any missing. Students' outcome data were not imputed. The HLM controlled for student demographic characteristics and prior achievement scores.
Effect sizes for continous outcomes are reported using Hedge's g. Effect sizes for categorical outcomes are reported using Cox's index.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Due to our concerns about selection bias, we applied the method described by Frank et al. (2013) to our results as a type of sensitivity analysis. This method allows us to quantify the amount of bias associated with nonrandom assignment to treatment necessary to invalidate the inference that health pathway participation increased students' high school credits earned, number of a-g requirements met, high school graduation, and college enrollment as compared to students in traditional high school programs. In the Frank et al. (2013) framework, the robustness of an inference is a function of the percentage of the impact estimate that exceeds a threshold that would render the estimate statistically not significant. The estimated effect of health pathway participation on credits earned is 7.8, with a standard error of 2.9. The threshold for statistical significance of this estimate at the .05 level is therefore 5.7 = 2.9*1.96. Using Frank et al.'s formula (estimate−threshold)/estimate, we calculated the percent bias that would invalidate the inference to be 27 percent = (7.8–5.7)/5.7. This means that to invalidate the inference that health pathway participation had a positive effect of increasing credits earned on the full sample of students, 27 percent of the estimated effect would have to be due to bias. In other words, 27 percent of the health pathway student sample would have to be replaced with students for whom health pathway participation had zero effect on them in order to invalidate the inference that health pathway participation had a positive impact on credits earned.

This analysis provides evidence of the relative robustness of the estimated impact. The amount of bias that would be needed to invalidate the inference for number of a-g requirements met, high school graduation, and college enrollment are 7 percent, 25 percent, and 27 percent, respectively. These bias analyses suggest that for three of the four outcomes, a very high level of selection bias would be needed to negate the entirety of our estimated treatment effects; therefore the effects are less likely to be strictly an artifact of selection bias. This allows us to have more confidence that our estimated treatment effects are not entirely spurious. However, it does not allow us to ascertain the degree to which our treatment effects are inflated due to selection bias.

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