Impact Evaluation of the Minnesota Alliance With Youth Statewide AmeriCorps Promise Fellows Program

Prepared for Minnesota Alliance With Youth on October 7, 2022 by Ethan R. Van Norman, PhD

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Background

The Promise Fellow Program is an intervention designed to prevent dropout amongst students in grades 6-12 in Minnesota that show early warning signs of school disengagement.

The program consists of three components, led by interventionists, or Promise Fellows. The program draws from a menu of research-based supports. Each category of support, caring adults, service-learning, and out-of-school supports align with the National Dropout Prevention Center's "Basic Core Strategies".

Caring adult strategies aim to develop strong, positive relationships between the student and the Promise Fellow as well as other adults in the student's life. Service-learning involves the Promise Fellow helping the student serve as a mentor, volunteer, or to engage in a service-learning project. Finally, for out-of-school supports, the Promise Fellow helps the student participate in things like after-school clubs, activities, and tutoring.

Each Promise Fellow generally supports at least 30 youth for a minimum of 12 weeks. Promise Fellows regularly meet with the Youth Success Team, where data collected by Fellows (e.g., Attendance, Engagement, Work Completion) are shared to create a focus list and develop targeted supports based upon student need.

Present Evaluation

The purpose of this report is to evaluate the impact of the Promise Fellow Program on student school attendance. More specifically, this report will determine whether there is a statistically significant difference in the percentage of days attended between students served by the Promise Fellow Program and students not served by the program during the 2021-2022 academic year. In addition, this report will explore the impact of the Promise Fellow Program on school attendance for various student subgroups including gender, race, and grade level.

Data from 2021-2022

At the conclusion of the 2021-2022 academic school year, a total of 11 schools that participated in the Promise Fellow Program shared attendance data with the Minnesota Alliance With Youth. The table below shows the number of students present in the dataset shared with the evaluator.

Table 1. Summary of Students Characteristics in Entire Dataset

School ID	Promise Fellow (n)	Typical Practice (n)	Total (n)
1	16	694	710
2	25	232	257
3	22	36	58
4	11	114	125
5	11	80	91
6	4	983	987
7	15	15	30
8	3	57	60
9	225	1086	1311
10	11	57	68
11	31	1956	1987
Total (%)	374 (6.58%)	5310 (93.42%)	5684

Demographic information for the entire sample as well as by Promise Fellow Program students and non-participating students (Typical Practice) are presented below:

Table 2. Demographic Information for Entire Sample

	Promise Fellow (n = 374)	Typical Practice (n = 5310)	Total (n = 5684)
Gender			
Female	3.96%	42.93%	46.89%
Male	2.52%	48.89%	51.41%
Other	0.11%	0.23%	0.33%
Not Reported	--	1.37%	1.37%
Grade			
5	--	0.12%	0.12%
6	0.48%	4.45%	4.93%
7	0.76%	12.30%	13.05%
8	1.02%	13.83%	14.85%
9	0.67%	19.16%	19.83%
10	1.20%	12.97%	14.16%
11	1.13%	13.48%	14.60%
12	1.34%	17.10%	18.44%
Not Reported	-	0.02%	0.02%
Race			
AI	0.14%	1.74%	1.88%
Asian	0.12%	4.68%	4.80%
Black	1.76%	11.59%	13.35%
Latinx	2.57%	13.37%	15.94%
Multi-Racial	0.14%	2.41%	2.55%
NHPI	-	0.05%	0.05%
Oromo	-	0.02%	0.02%
Somali	0.02%	1.06%	1.07%
White	1.83%	57.14%	58.97%
Not Reported	-	1.35%	1.35%

Note. AI – Native Alaskan / American Indian, NHPI – Native Hawaiian / Pacific Islander

Reviewing Tables 1 and 2 there is a clear imbalance in the number of students that participated in the Promise Fellow Program relative to students that did not. Combined with the fact that students were not randomly selected to participate in the program, statistical adjustments were necessary to determine the impact of the intervention.

Data Analysis Plan

Propensity score matching is a method in which the effect of an intervention can be estimated when students are not randomly assigned to conditions (Rosenbaum & Rubin, 1983). Random assignment in experiments helps to ensure that treatment and control groups are balanced on factors that may predict treatment response other than the intervention. Propensity score matching can be used to meaningfully select students that did not participate in the Promise Fellow Program to compare against students that did participate.

Propensity score matching, in general, matches students from the experimental group with those from the control group by estimating a logistic regression model in which relevant student characteristics are used to predict treatment assignment. Depending on the matching method used, students from each group are matched based upon their probability of receiving the treatment from the logistic regression analysis. Doing so reduces bias in the estimation of treatment effects caused by confounding factors that influence whether students were or were not selected to participate in the intervention.

For the present evaluation 1:1 nearest neighbor propensity score matching without replacement was conducted using the MatchIt package (Ho et al., 2011) in the computer program R (R Core Team, 2021). Data available for most students included grade level, race, gender, ethnicity, and the percentage of school days attended the previous year. One complexity in the present evaluation was the nested nature of outcomes. Namely, students were nested within schools. This is important because any number of unmeasured factors within individual school sites may have influenced student participation in the program. To account for this, propensity score matching was conducted separately within each school site (Cannas & Arpino, 2019).

Matching Process

Unfortunately, data from three schools (3, 7 and 10) could not be used for a variety of reasons including limited or no outcome data (end of year attendance rates) and/or large volumes of missing student data (e.g., race, gender). In addition, sites 8 and 9 did not have sufficient information to match students in grade five that participated in the program. In turn, those students were matched out of grade level within their sites.

There was a total of 309 students that participated in the Promise Fellow Program included in the analytic sample and 309 comparable peers that did not participate. The average attendance rate was 79.16% for the control group the previous year compared to an average rate of 78.19% in the Promise Fellow group. That difference was not statistically significant (t = 0.867) at the $p < .05$ level (p = .385).

Follow-up chi-square tests of independence suggest that groups did not differ as a function of gender ($\chi^2_{df=2}$ = 0.174, p = .917) or race ($\chi^2_{df=6}$ = 8.989, p = .174). This suggests that the matched groups are sufficiently comparable to permit an evaluation of the impact of the Promise Fellow Program.

Overall Impact

Given the nested nature of available data, a Generalized Estimating Equation (GEE) was estimated to quantify the overall average impact of participating in the program across available student characteristics and previous attendance history. By using a GEE the unique influence of each school site is statistically taken into account to determine the overall impact of the program (McNeish et al., 2017). The geepack package (Højsgaard et al., 2006) in the computer program R (R Core Team, 2021) was used for analyses.

Analyses for Student Sub-Groups

In addition to understanding the typical, or average, impact of the program on school attendance, follow-up analyses were conducted to determine whether the Promise Fellow Program differentially impacted student sub-groups. Separate logistic regression models were estimated to determine the impact of the program teased apart by gender, grade level, and race. These analyses considered the impact across school sites. Logistic regression analyses were conducting using the glm function in R (R Core Team, 2021).

Results

The Appendix shows the raw output of the GEE and logistic regression analyses. In each case a binomial link function was used to model the percentage of school days students attended in the academic year with weights equal to the number of days school was in session. The output of those analyses, log-odd coefficients, are difficult to interpret. Therefore, in the main report log-odds are converted to probabilities which are converted to percentages to quantify the average percentage of schooldays attended for each group of interest. In addition, assuming a 170-day academic year, the average number of days differences in percentages translate to are also reported.

Overall Impact of Promise Fellow Program

Table 3. Overall Change in Attendance Percentage

Typical Practice	Promise Fellow	Difference	Difference (School Days)
80.38%	83.20%	+ 2.82%	+ 4.79

The results of the GEE suggest that the net effect, or overall average effect of the program yielded a statistically significant ($p < .001$) difference in the attendance rates of students that participated in the Promise Fellow Program compared to students that did not. Converting the outcomes of that analysis suggest that, on average, students that participated in the program **attended one more week, or roughly five days of school**, relative to students that did not participate in the program (assuming a 170 day school year).

Impact of the Promise Fellow Program across Student Sub-Groups

Table 4. Change in Attendance Percentage by Grade Level

Grade	Typical Practice	Promise Fellow	Difference	Difference (School Days)
7	82.55	83.26	+0.71	+1.21
8	86.33	80.60	-5.73	-9.74
9	84.08	86.92	+2.84	+4.83
10	82.16	85.08	+2.92	+4.96
11	76.24	83.4	+7.16	+12.17
12	74.36	80.85	+6.49	+11.03

The results of this analysis suggest the program is relatively **most impactful for older students.** Note low participation rates in grade five and six forced them to be omitted from this follow-up analysis.

Table 5. Change in Attendance Percentage by Gender

Gender	Typical Practice	Promise Fellow	Difference	Difference (School Days)
Female	80.83	83.64	+2.81	+4.77
Male	79.93	83.01	+3.08	+5.24

The results of this analysis suggest that the program works **similarly for male and female students.** Note there were a few students that identified as non-binary in the sample that could not be adequately matched within individual school sites.

Table 6. Change in Attendance Percentage by Race

Race	Typical Practice	Promise Fellow	Difference	Difference (School Days)
AI	79.87	73.52	-6.35	-10.80
Asian	85.22	91.16	+5.94	+10.10
Black	80.98	81.35	+0.37	+0.63
Latinx	78.40	84.20	+5.80	+9.86
Multi	82.72	89.44	+6.72	+11.42
White	82.62	83.45	+0.83	+1.41

Note – AI: American Indian. Only racial categories with a sufficient sample size were included.

The results of this analysis suggest that the program tends to have **differential impact as a function of student race.** Namely, American Indian students that participated in the program attended school less than non-participants. Black students tended to experience little increase in school attendance whereas the program seems to be relatively more effective for students that were Asian, Latinx, and multi-racial.

Summary of Program Impact

Overall, the results of this impact evaluation suggest that the Promise Fellow Program had on average, a **statistically significant positive** effect on school attendance for students that participated.

Further, the program seems to be relatively most effective for students at higher grade levels, as well as Asian, Latinx, and multi-racial students.

Moving forward, it may be worthwhile to conduct internal reviews to determine how the program may be optimized for younger students as well as American Indian and Black students.

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Appendix

Table 7. Generalized Estimating Equation Output for Overall Program Impact (Log-Odd Units)

Coefficient	*B*	SE	Wald	*p*
Intercept	1.410	0.027	2645.44	<.001
Treatment	0.191	0.037	26.396	<.001

Table 8. Logistic Regression Analysis for Impact of Grade Level (Log-Odd Units)

Coefficient	*B*	SE	*p*
Intercept	1.554	0.027	<.001
Treatment	0.053	0.043	.219
Grade 8	0.289	0.045	<.001
Grade 9	0.109	0.430	.011
Grade 10	-0.028	0.038	.470
Grade 11	-0.388	0.039	<.001
Grade 12	-0.485	0.035	<.001
Grade 8 x Treat	-0.469	0.062	<.001
Grade 9 x Treat	0.183	0.075	.014
Grade 10 x Treat	0.161	0.058	.005
Grade 11 x Treat	0.398	0.058	<.001
Grade 12 x Treat	0.322	0.055	<.001
Model Fit	**Deviance (Null)**	**Deviance (Residual)**	**AIC**
	10168.30	9316.80	1221

Table 9. Logistic Regression Analysis for Impact of Gender (Log-Odd Units)

Coefficient	*B*	SE	*p*
Intercept	1.440	0.015	<.001
Treatment	0.193	0.021	<.001
Male	-0.056	-0.057	.023
Male x Treat	0.013	0.014	.681
Model Fit	**Deviance (Null)**	**Deviance (Residual)**	**AIC**
	10539	10159	13175

Coefficient	*B*	SE	*p*
Intercept	1.379	0.191	<.001
Treatment	-0.357	0.202	.077
Asian	0.373	0.206	.070
Black	0.066	0.194	.733
Latinx	-0.093	0.192	.630
Multi	0.189	0.224	.405
White	0.180	0.193	.351
Treat x Asian	0.938	0.248	<.001
Treat x Black	0.381	0.205	.062
Treat x Latinx	0.741	0.204	<.001
Train x Multi	0.923	0.265	<.001
Train x White	0.416	0.204	.042
Model Fit	**Deviance (Null)**	**Deviance (Residual)**	**AIC**
	10539	10036	13066

Table 10. Logistic Regression Analysis for Impact of Race/Ethnicity (Log-Odd Units)