What Makes a Difference in Attendance?

Analysis of Four Years of Data at North Queens Community High School

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Summary

Since adopting the PowerSchool student information system four years ago, staff members at North Queens Community High School, a school serving over-aged under-credited high school students in the Kew Gardens section of Queens, have consistently used this system to track students' attendance, grades, and behavioral interventions. In fact, in those four years more than 30,000 behavioral interventions and every student's attendance in every class every day have been recorded. This wealth of data allows us to ask a question using statistical analysis that advocate counselors and school leaders attempt to answer anecdotally every day: *What makes a difference in attendance?* Our six key findings are as follows:

1. **Attendance begets attendance.** While we may have hoped to find other "silver bullets" inherent to students that could help us predict which ones would have better or worse attendance or be more or less responsive to interventions, we found instead that by far the single most powerful determinant of current attendance is past attendance.
2. **Impact lasts.** Immediate effects of outreach interventions on attendance appear to persist not just over a few days, but over several weeks following the intervention.
3. **Reach down to pull up.** When it came to response to interventions, students with worse attendance had better results.
4. **The power interventions.** Counseling (whether recorded as a counseling session, career advice, or college advice) and talking to guardians (most of all through a meeting but also through a call) have noticeably more impact than attendance outreach phone calls, even for students with low prior attendance.
5. **Call or visit.** Home visits have no greater impact than attendance outreach calls.
6. **The middle is the hardest part.** Students responded most positively to interventions in Benchmarks 5 and 6. In contrast, responsiveness was at its worst (though not far worse) in Benchmarks 2 and 3.

Since adopting the PowerSchool student information system four years ago, staff members at North Queens Community High School, a school serving over-aged under-credited high school students in the Kew Gardens section of Queens, have consistently used this system to track students' attendance, grades, and behavioral interventions. In fact, in those four years more than 30,000 behavioral interventions and every student's attendance in every class every day have been recorded. This wealth of data allows us to ask a question using statistical analysis that advocate counselors and school leaders attempt to answer anecdotally every day: *What makes a difference in attendance?*

Methodology

To answer our question, we used a multivariate regression analysis. The advantage of using this statistical analysis is that it allows us to look at any particular factor, controlling for others. We are able to ask, for instance, "All other things equal, if a student is male, how much better or worse do we expect their attendance to be than if they were female?"

The question, *What makes a difference in attendance?* is not a simple one. First, we must define what we count as "making a difference." We divided this into three questions: Which factors relate to students' attendance over an entire term (which we label "Overall" attendance)? Which factors relate to students' attendance for just 3 days after an intervention (which we label "Response," since this is most likely the immediate response to a particular intervention)? Which factors relate to students' attendance over 20 days after an intervention (which we label "Persistence," since it reflects the persistence of a student's attendance following a particular intervention)?

In our findings, we focus particularly on Overall Attendance and Persistence. We do this because these yielded R^2 values of, respectively, 0.57 and 0.54. This means that the variables we included explained 57% and 54% of the resulting attendance. The R^2 value for Response to Intervention, however, was much lower at 0.29, suggesting that there are other unexplained factors that affect attendance when viewed in such a brief timeframe.

Second, we had to define attendance. In the analysis, attendance is counted not simply as a student's recorded homeroom attendance, but rather as their attendance period by period throughout the day. A student who is absent for half the day then appears as having 50% attendance for that day. It is important to note that period attendance is not always entirely accurate, but data comparing this to homeroom attendance reveals that homeroom attendance, too, is not always accurate (nor, for that matter, unfortunately, is attendance on record with the Department of Education, even if this is what is used for accountability purposes). Given the realities of human error, it appears that there is greater benefit to the precision of using period attendance than homeroom attendance.

Figures for attendance were then analyzed against a variety of independent variables that could feasibly affect them, including: specific behavioral interventions, the number of behavioral interventions in a term, counselors, cumulative credits, credits earned previous term, number of failing grades, daily attendance prior term, period attendance in the 3 days prior to intervention, age, year in school, gender, special education status, timing of intervention within each term, and timing of intervention in days of the week. Because of the vast amount of data available, almost every one of these variables was found to have a statistically significant impact on attendance (table at end of this report). Our question was then not simply what had an impact (almost everything did), but rather what had the largest impact. The key findings that follow focus on the question of size of impact.

Findings

Finding #1. Attendance begets attendance

By first looking at Overall Attendance, we can ask what factors *outside of* behavioral interventions seem to have an impact, since it would be hard to imagine a single behavioral intervention having a strong impact on an entire term, whereas a student's gender or year in school may.

In fact, gender and year in school *do* have a statistically significant impact on attendance, as do credits earned in the prior term, cumulative credits at start of the term, and special education status. However, every one of these is so small as to be negligible, and some may be contrary to what would have been expected. In fact, the only factor that has a major impact on current attendance is: prior attendance. While this may sound obvious at first, it is in fact a worthwhile discovery. **While we may have hoped to find other "silver bullets" that could help us predict which students would have better or worse attendance or be more or less responsive, we found instead that the single most powerful determinant of current attendance is past attendance.**

Starting with prior attendance, we provide below specific examples of impact on attendance for every appropriate variable in our analysis that had a $p<.01$ level of significance or higher:

- All other things equal, if we compare a student whose attendance in the prior term was 60% with one whose attendance in the prior term was 50%, the student with 10 point higher attendance in the prior term would have attendance 7.4 points higher in the current term.
- All other things equal, if we compare a student who earned 4 credits in the prior term with a student who earned 2 credits, the student with higher credits in the prior term would have attendance 3.7 points higher.
- All other things equal, males had attendance 2.3 points higher than females.
- All other things equal, students with IEP's had attendance 1.1 points higher than those without.
- All other things equal, a student who started the term with 15 credits had attendance 1.1 points higher than a student who started the term with 5 credits.
- All other things equal, a student in their third year at NQCHS had attendance 0.24 points higher than a student in their second year.

Our remaining findings focus not on Overall Attendance, but instead in Persistence in Attendance following interventions. This allows us to ask what affect interventions appear to have on attendance. Many initial findings (not included below) are not particularly surprising: Among them, students failing more classes are less responsive to interventions, as are students who have earned fewer credits in the past. Five findings, however, do stand out. These are highlighted below:

Finding #2. Impact lasts

Immediate effects of outreach interventions on attendance appear to persist over the month following. In most cases, coefficients remained approximately the same when comparing immediate 3-day response to month-long persistence (though some decrease in the effects of Guardian Meetings is noticeable). This suggests that the impact of most interventions lasts not just for a few days but for several weeks.

Finding #3. Reach down to pull up

Students with worse attendance had better results. As stated above, various demographic factors had significant but small impact on attendance. This was true for Responsiveness and Persistence in attendance, just as it had been true for Overall attendance. The one dramatic difference is key: If you are looking at Overall attendance, students who had worse attendance tended to continue doing worse. If, on the other hand, you are looking at Persistence in changes in attendance, students who were doing worse initially showed better improvements than students who were doing better.

For example, imagine a counselor is working with two students who are exactly the same except that one had attended 30% of their classes in the last 3 days and the other had attended 60% of their classes in the last 3 days. The counselor engages in the same intervention with both students. The data suggests that the student who had attended 30% of their classes will have an 18-point bigger improvement in their attendance in the next 20 days than the student who had 60% attendance. Some of this may be the result of "regression to the mean" – that is, students with lower attendance simply have more room to improve. However, the coefficient is large enough to suggest that it is more than that: students with low attendance are responding more dramatically to interventions.

Finding #4. The power interventions

Counseling and talking to guardians are far more effective than attendance outreach, even for students with low prior attendance. The five clearly defined interventions that appear to have the greatest impact on attendance are (in order): guardian meetings, college advice, career advice, counseling, and guardian calls. This holds true even when looking at students whose attendance prior to the intervention was at the level of just 10% or 20%, which is to say that we do not appear to be simply identifying students who had strong attendance to start with, but rather are seeing that no matter what their prior attendance, students saw a big bump in attendance in the next 20 days if they engaged in one of these interventions.

All other things equal, guardian meetings led to a 4- to 5-point greater increase in attendance than an attendance outreach call in which the counselor speaks to the student. Talking to a guardian by phone led to a 2- to 3-point greater than talking to a student by phone. For different forms of guidance (counseling, career advice, and college advice), the increase is 3 to 4 points greater than talking with the student by phone.

Finding #5. Call or visit

Home visits have no greater impact than attendance outreach calls. There is no statistical difference in the impact of a home visit versus an attendance outreach call in which a message is left on an answering machine.

Finding #6. The middle is the hardest part

Students responded most positively to interventions in Benchmarks 5 and 6. By including in the regression the benchmark during which an intervention occurred, we were able to ask the question: Is students' responsiveness to interventions affected by benchmark? The answer appeared to be a moderate yes. The data suggest that if you are going to engage in an intervention, you will get the greatest impact, by far, in Benchmark 6, slightly less in Benchmark 5, and your third choice should be in Benchmark 1. Benchmarks 2 and 3 appear to be the worst times for interventions to have an impact.

Independent Variables		Dependent Variables		
		Overall	Response	Persistence
		% Attendance for Term (daily)	Change in % Attendance for 3 Days Following Intervention (period)	Change in % Attendance for Month Following Intervention (period)
Student Supports				
Number of Interventions per Term		0.01 **	-0.11 ***	-0.10 ***
Intervention Type [1]				
	AO 407		-3.43 ***	1.96 ***
	AO Home Visit		0.66	0.30
	AO Court/Emergency/Medical		0.09	0.28
	AO Blank		0.54	-0.22
	AO No Answer/Phone Disconnect		-1.85 ***	-1.34 ***
	AO Other		7.14 ***	4.59 ***
	AO Running Late		1.81 ***	1.20 ***
	AO Sick		0.01	0.48
	AO Transit/Overslept/Home/Child		3.75 ***	1.83 **
	AO Unknown Whereabouts		0.63	-0.94 **
	Behavior		0.16	2.94 ***
	Career Advice		6.11 ***	4.47 ***

	College Advice			5.32	***	4.91	***
	Counseling			4.56	***	4.43	***
	Guardian Call			3.00	***	3.40	***
	Guardian Meeting			8.61	***	5.98	***
	Other log (not AO Call)			7.37	***	7.19	***
Counselor [2]							
	Zoraida	-1.84	***	-1.35	***	-2.14	***
	Annette	0.16		0.92	*	1.75	***
	Francesca	-0.16		0.91	*	1.57	***
	Chris D	0.98	***	-2.25	***	-2.22	***
	Fritz	1.96	***	2.50	***	3.94	***
	Jenny	-1.01	***	1.12	***	1.71	***
	Tanell	3.55	***	8.38	***	7.87	***
	Asmah	-2.29	***	-0.12		0.25	
	Ryan	0.08		7.72	***	7.00	***
	Michael	-1.30	***	-1.85	***	-1.53	***
Academics							
	Cumulative Credits at Start of Term	0.11	***	0.13	***	0.14	***
	Credits Earned in Prior Term	1.84	***	0.55	***	0.49	***
	# of Course Grades <65 in Benchmark Prior			-1.74	***	-1.58	***
	Daily Attendance in Prior Term	0.74	***	0.16	***	0.16	***
	Period Attendance in 3 Days Prior			-0.58	***	-0.61	***
Demographics							
	Age at Start of Term	0.10	*	0.16		0.25	***
	Year in School	0.24	***	0.23		0.36	***
	Gender (Male)	2.33	***	0.57	**	0.08	
	SPED	1.10	***	-1.24	***	-0.76	***
Timing of Intervention [3]							
	Benchmark 2			-1.04	***	0.52	**
	Benchmark 3			-0.89	**	1.01	***
	Benchmark 4			-0.39		1.10	***
	Benchmark 5			1.16	***	9.04	***
	Benchmark 6			7.57	***	19.68	***
	Tuesday			-0.68	*		
	Wednesday			-0.64	*		
	Thursday			-1.44	***		
	Friday			0.35			
	Saturday/Sunday			-0.77			
Controls [4]							
	Year 2008	4.13	***	4.22	***	3.89	***
	Year 2009	1.89	***	5.51	***	4.62	***
	Year 2010	1.80	***	3.83	***	3.37	***
	Term 2	-23.21	***	-4.49	***	-3.01	***
	Term 3	-14.79	***	-0.94	**	2.74	***
Constant		15.80	***	17.91	***	12.89	***
Number of Observations		105,557		35,126		35,126	
Adjusted R-squared		0.57	***	0.29	***	0.54	***

[1] Coefficients show comparison to AO Left Message as most common intervention
[2] Coefficients show comparison to Renatta as most common counselor
[3] Coefficients show comparison to Benchmark 1 and Monday, respectively
[4] Coefficients show comparison to Year 2011 and Term 1, respectively

*** Significant at the 99% level (p<0.01)
** Significant at the 95% level (p<0.05)
* Significant at the 90% level (p<0.10)