A Retrospective Examination of Student Success Hub Effects on Student Success Pre- and Post-Implementation

Shelby Hagle
The Evaluation Center, Western Michigan University

Introduction

Background

The Student Success Hub (SSH) is a centralized location for students to meet all of their success needs, including accessing support services, making appointments with support staff on campus, getting personalized support plans, and most important to this study, where students can receive and view their alerts that may be putting their success at risk (Western Michigan University, n.d.). On the back end, SSH gives support staff a single management system for tracking and addressing student alerts, allowing the university to streamline the process of supporting students based on their current success needs, as identified by the alert (Flynn, March 14, 2023). Students can receive an alert for any number of reason, grouped into various categories, including Advising Alerts, Thriving Alerts, Navigator Alerts, and Student Concern Form Alerts. Other information collected includes student's various appointments and visits to success-related programs, such as their number of Wellness appointments or their number of visits to the Bronco Study Zone in a semester.

In addition to information on student alerts, WMU also maintains record of many other academic related characteristics for students from both their high school academic records and their collegiate academic records, and sometimes utilizes this information to generate insights on student success. For high school, this includes measures of students number of AP courses taken and graduating high school GPA; at the collegiate level, this also includes courses students have taken, midterm and final grades reported for those courses, students pass or fail status for the course, and various GPA metrics including a GPA at the start of the semester, a semester specific GPA, and cumulative GPA. These are not exhaustive lists of academic records used to measure student success, however, these are the relevant factors examined in this examination.

Problem

With the amount of resources being utilized to operate SSH, it is important to consider the impact SSH is having not only on students, but how it is paving the way to help improve student success and retention at WMU. Analysis of student success metrics in conjunction with the SSH generated alerts are already underway at WMU, but one crucial piece of information that is missing is the true impact SSH had had since its implementation. While we do not have the full array of data that SSH currently offers to examine comparatively from a retrospective point of view, there are datapoints that universities maintain records of that we can use to examine impact on various success metrics.

Purpose and Goals

The purpose of this study was to examine the impact that the Student Success Hub has had on various metrics of student success. Our goal is to identify differences in these metrics from pre- and post-implementation of the Hub by examining historical data points in comparison with current data collected from SSH in order to understand its efficacy on student success.

Research Questions

Our overall goal for this study is to evaluate the effectiveness of SSH in improving student success metrics since its implementation. Given this goal, our research questions are as follows:

1) Is there a change in the rate at which midterm grades are being provided following the implementation of SSH?
    a. Of those students with grades provided, is there a change in the rate of low midterm grades being received over time?
    b. Are we able to predict if a student receives a flag for having a low midterm grade?
        i. Is there a difference in these predictions pre- and post- implementation of SSH?
    c. Are we able to predict the number of low midterm grades a student receives?
        i. Is there a difference in these predictions pre- and post- implementation of SSH?
2) Does persistence/retention change following the implementation of SSH?
    a. Is there a change in the difference of persistence/retention for students with and without midterm grade alerts?
    b. Are we able to predict persistence/retention?
    c. Is there a difference in these predictions pre- and post- implementation of SSH?
3) Does the proportion of courses not passed decrease following the implementation of SSH?
    a. Is there a change in the difference in proportion of courses not passed for students with and without midterm grade alerts?
    b. Are we able to predict proportion of courses not passed?
    c. Is there a difference in these predictions pre- and post- implementation of SSH?
4) Does End of Semester GPA improve following the implementation of SSH?
    a. Is there a change in the difference in End of Semester GPA for students with and without midterm grade alerts?
    b. Are we able to predict end of semester GPA?
    c. Is there a difference in these predictions pre- and post- implementation of SSH?
5) Do these changes in success metrics exist amongst varying student characteristics?
    a. Do these characteristics aid in the prediction of our four success metrics?
    b. Is there a difference in these predictions pre- and post- implementation of SSH?

To answer these research questions, the results section has been broken down by dependent variable of interest: Low Midterm Grades, Persistence/Retention, Proportion of Courses not Passed, and End of Semester GPA. These correspond with Research questions 1 – 4 and their sub questions. Research question 5 is answered throughout research questions 1-4, as it asks about the inclusion of student characteristics in the models, which is done throughout all of the analyses.

Methods

This research follows a quantitative methodology utilizing descriptive statistics, logistic regression, and multiple linear regression as the main forms of analyses. This study was conducted using data from the academic years spanning from 2019 to 2024.

Sample

Given that we are examining students across a number of different time periods, descriptive statistics will be reported for the overall sample, pre- and post-implementation of SSH, shown in Table 1. The overall sample for this research includes N = 85,469 individuals; for PreSSH and PostSSH, the sample included n = 60,143 and n = 25,326, respectively. From 2019 to 2024, the sample sizes, by year were as follows: n_{2019} = 16,801, n_{2020} = 15,698, n_{2021} = 14,301, n_{2022} = 13,334, n_{2023} = 12,746, and n_{2024} = 12,580.

Table 1

Sample Demographic Characteristics

	Overall Sample		**PreSSH**		**PostSSH**	
	n	*%*	*n*	*%*	*n*	*%*
Sex / Gender						
Female	42682	49.9%	29746	49.5%	12936	51.1%
Male	42787	50.1%	30397	50.5%	12390	48.9%
Race / Ethnicity						
American Indian / Alaska Native	331	0.4%	245	0.4%	86	0.3%
Asian	2047	2.4%	1355	2.3%	692	2.7%
Black / African American	7824	9.2%	5799	9.6%	2025	8.0%
Hispanic	7058	8.3%	4745	7.9%	2313	9.1%
International	4475	5.2%	3358	5.6%	1117	4.45
Native Hawaiian / Pacific Islander	54	0.1%	42	0.1%	12	0.0%
Two or More Races	3419	4.0%	1035	1.7%	1141	4.5%
White	58652	68.6%	41286	68.6%	17366	68.6%
Not Reported	1609	1.9%	1035	1.7%	574	2.3%
FTIAC						
Yes	14952	17.5%	10093	16.8%	4859	19.2%
No	70517	82.5%	50050	83.2%	20467	80.8%
Persistence / Retention						
Retained / Graduated	78730	92.1%	55094	91.6%	23636	93.3%
Not Retained	6739	7.9%	5049	8.4%	1690	6.7%
Academic College						
Arts & Sciences	18995	22.2%	13360	22.2%	5635	22.2%
Aviation	6600	7.7%	4521	7.5%	2079	8.2%
Education & Human Development	9683	11.3%	7023	11.7%	2660	10.5%

Engineering & Applied Sciences	12058	14.1%	8468	14.1%	3590	14.2%
Extended University Programs	1225	1.4%	1034	1.7%	191	0.8%
Fine Arts	7041	8.2%	4532	7.5%	2509	9.9%
Haworth College of Business	18165	21.3%	12951	21.5%	5214	20.6%
Health & Human Services	8531	10.0%	6148	10.2%	2383	9.4%
Merze Tate College	1576	1.8%	515	0.9%	1061	4.2%
Other	1595	1.9%	1591	2.6%	4	0.0%
Midterm Grade Reported						
Yes	77204	90.3%	59560	89.1%	23644	93.4%
No	8037	9.4%	6379	10.6%	1658	6.5%
Missing	228	0.3%	204	0.3%	24	0.1%

Note. Overall N = 85,469; PreSSH n = 60,143; PostSSH n = 25,326.

Analysis Tools

Microsoft Excel was used for cleaning and preparing the data prior to its use in SPSS for analysis, as well as for some descriptive analyses. SPSS was used for all other analyses and also included assumptions testing and variable recoding.

Analyses

For this research, descriptive statistics, frequencies, correlations, data imputation, logistic regression, and multiple linear regression were all conducted to examine our research questions. Our primary dependent variables of interest include Low Midterm Grade Flag, Low Midterm Grade Count, Persistence/Retention, Proportion of Courses Not Passed, and End of Semester GPA. These dependent variables were examined against multiple metrics from student academic profiles and student characteristics. Given our extensive sample sizes of over n = 10,000, only values that were significant at the .001 level were considered for significance. This is to help combat significance inflation due to sample size. Given this information, interpretable "fit" statistics are more telling and reliable than p-values alone for this study.

Data Imputation

High School GPA was a primary variable of interest for this study in reference to our FTIAC population. In order to complete the analyses on this population using all data points at our disposal, data imputation was completed to fill in missing data on our original High School GPA Variable. Multiple Imputation in SPSS was utilized for this procedure using the Fully Conditional Specification method with 20 iterations to ensure convergence. Because this dataset uses repeated individuals as unique datapoints, matching the imputed high school GPA to a repeated individuals profile across all of their missing datapoints was crucial, making the FCS method ideal. A students unique ID, their AP course count, and FTIAC status were all used as independent variables when setting up constraints for imputation to ensure that profiles were matched appropriately. Once data was imputed and examined, the newly imputed high school GPA variable was transformed to allow all reported values to operate functionally in the dataset. Some data points were extreme outliers, as their values utilize a different scale than the traditional 5.0 standard GPA scale; for some cases, these data were also marked as missing. Descriptive statistics on the high school GPA variables can be found below.

Table 2
Descriptives on Imputed Transformed Variables

	Original HS GPA Variable	**Imputed HS GPA Variable**	**Imputed, Transformed HS GPA Variable**
n	69985	85469	85460
M	3.472	3.445	3.433
SE	.008	.007	.002
SD	2.125	1.956	0.540
Min	.150	.150	.150
Max	380.000	380.000	6.220
Range	379.850	379.850	6.070
Variance	4.517	3.828	0.292
Skewness	160.288 (.009)	169.060 (.008)	-0.330 (.008)
Kurtosis	28197.329 (.019)	32201.491 (.017)	0.010 (.017)

Descriptives & Frequencies

Frequencies were created in Excel and SPSS to examine all research questions in order to explore relationships between student success metrics, student characteristics, and academic profile metrics across time.

Correlation

Correlation analysis was used to examine the relationship between our student success outcome metrics and various metrics from student academic profiles. Correlations were primarily used as a guide in our model building process. See Correlation Matrix in Appendix B.

Logistic Regression

Logistic regression was used to analyze part of research question 1 assessing whether we are able to predict a student receiving a flag for low midterm grade. Logistic regression was also used to analyze research question 2 examining student persistence/retention. Both of these examinations also included an examination across time and included an exploration of the influence of student characteristics (research question 5). Dichotomous variables were created for student persistence/retention and for having received a low midterm grade and were used as dependent variables against multiple predictors from student characteristics and their academic profiles.

Multiple Linear Regression

Multiple linear regression was used to analyze part of research question 1 assessing whether we are able to predict the number of low midterm grades a student receives. Multiple linear regression was also used to examine research questions 3 and 4 assessing the proportion of courses not passed, and end of semester GPA. Both of these examinations also included an examination across time and included an exploration of the influence of student characteristics (research question 5). End of semester GPA, Low midterm grade count, and Proportion of courses not passed were all examined as dependent variables across the modeling process and were examined against multiple predictors from student characteristics and their academic profiles.

Variable Recoding. In order to create logistic regression models, multiple variables were recoded into dichotomous variables to make them functional and interpretable in the regression analysis. This includes students college of belonging, gender, and race/ethnicity. For a full list of recoded variables, see Appendix A.

Model Building. All regression models were built using backwards selection methods. The original variables of interest for each of our questions were first put into a model to test for significance, where all student characteristic variables were then put into the model. The model was ran, removing one nonsignificant variable at a time based on the lowest t-value from the original model until all remaining variables in the model were significant. This allows us to find our best fitting model.

Results

Given that we are interested in retrospectively examining the effect of student success hub on measured student success, different metrics of interest were selected that could be matched to both the pre-implementation and post-implementation periods of SSH. Prior to the implementation of SSH, far fewer academic based metrics were recorded at the student level across courses and academic periods, meaning we had to measure the efficacy of SSH using the metrics we had available to us across both periods in order to make the results interpretable. This resulted in four major dependent variables of interest: Midterm Grades, Retention/Persistence, Proportion of Courses not Passed, and End of Semester GPA. In addition, we were also interested in these dependent variables within certain specific populations, such as for FTIAC students.

To measure the desired effect, data were examined for all students across all years in the total sample, by academic year, and Pre- and Post-Implementation of SSH. For our research questions interested in the predictability of student outcomes across these various measurement periods, this resulted in around nine regression models for comparison for each individual set of variables being examined: All Students, Pre-SSH, Post-SSH, 2019, 2020, 2021, 2022, 2023, and 2024. With this information in mind, results will be broken down first into sections by dependent variable, and then by analysis, as opposed to the traditional by analysis breakdown format. This is to keep results for relevant variables together and promote clarity in interpretations.

Results Section 1: Midterm Grades

Table 3

Rate of Midterm Grade Reporting Over Time

		Midterm Grade Reported?		
	n	No	Yes	% Change
All Students	85469	9.4%	90.3%	-
Pre-Post SSH				
Pre-SSH	60143	10.6%	89.1%	-
Post-SSH	25326	6.5%	93.4%	4.3%
By Year				
2019	16801	10.0%	89.6%	-
2020	15698	9.0%	90.7%	1.1%
2021	14310	7.0%	92.7%	2.0%
2022	13334	17.2%	82.5%	-10.2%
2023	12746	7.7%	92.2%	9.7%
2024	12580	5.4%	94.5%	2.3%

Note. All Time periods had missing values accounting for 0.1% – 0.4% of data.

For the overall data sample, midterm grades were reported a little more than 90% of the time. When examining by Pre- and Post-Implementation of SSH, there is a clear improvement in the rate at which midterm grades were reported for students, increasing by over 4% from an 89.1% to 93.4% rate of reporting. When examining the data by year, we can also see a gradual increase in the rate of reporting for all years except 2022, which represents an anomaly in the data. This could be due to changes in the reporting methods and requirements, and also represents the time when SSH was being transitioned to for the university. It should be noted that a significant portion of the data from 2022 was not reported as missing for the examination of this research question, with only 0.3% being marked as missing. Further investigations on 2022 data will need to be examined to determine a specific cause. From 2019 we see an 89.6% reporting rate, which increases to a 94.5% reporting rate by 2024.

Table 4

Midterm Grades Reported by Student Characteristics Pre- and Post-SSH

	PreSSH		PostSSH		
	No	Yes	No	Yes	% Change
All Students	10.6%	89.1%	6.5%	93.4%	4.3%
FTIAC Status					
NonFTIAC	12.5%	87.1%	8.0%	91.9%	4.8%
FTIAC	1.1%	98.8%	0.5%	99.5%	0.7%
Gender					

Female	10.0%	89.7%	5.5%	94.4%	4.7%
Male	11.2%	88.4%	7.6%	92.3%	3.9%
Race/Ethnicity					
American Indian / Alaska Native	13.5%	86.5%	3.5%	96.5%	10.0%
Asian	10.3%	89.4%	5.8%	94.2%	4.8%
Black / African American	8.8%	90.4%	5.6%	94.4%	4.0%
Hispanic	9.4%	90.2%	7.0%	92.8%	2.6%
International	14.6%	85.0%	10.8%	89.1%	4.1%
Native Hawaiian / Pacific Islander	9.5%	88.1%	8.3%	91.7%	3.6%
No Response	12.7%	87.0%	17.2%	82.6%	-4.4%
Two or More Races	9.6%	90.3%	3.9%	96.1%	5.8%
White	10.7%	89.1%	6.2%	93.7%	4.6%
By College					
Arts & Sciences	8.1%	91.7%	5.1%	94.8%	3.1%
Aviation	9.1%	90.8%	3.8%	96.2%	5.4%
Education & Human Dev.	11.3%	87.7%	7.1%	92.7%	5.0%
Engineering & Applied Sciences	13.3%	86.5%	12.5%	87.5%	1.0%
E.U.P.	18.7%	79.8%	16.8%	83.2%	3.4%
Fine Arts	10.7%	88.9%	5.6%	94.3%	5.4%
Haworth College of Business	12.2%	87.5%	6.2%	93.7%	6.2%
Health & Human Services	10.5%	89.4%	3.9%	96.1%	6.7%
Merze Tate College	7.2%	92.8%	6.3%	93.5%	0.7%
Other	1.8%	98.1%	50.0%	50.0%	-48.1%

For a comparison of FTIAC vs NonFTIAC students, we see that midterm grades both Pre- and Post-SSH are reported at a higher rate for FTIAC students versus the NonFTIAC students. Additionally, for both groups, we see an increase in the rate at which midterm grades were reported, increasing by nearly 5% for NonFTIAC students, and increasing by 0.7% for FTIAC students. While the growth shown in the rate of reporting for FTIAC seems low, their original reporting rate was at nearly 99% prior to the implementation of SSH, leaving little room available for growth.

When comparing across genders, we can see that females had a higher rate of midterm grades being reported compared to males both Pre- and Post-SSH implementation; we can see an increase in the rate of midterm grades being reported for both females (4.7%) and males (3.9%) following the implementation of SSH.

When comparing across races/ethnicities, we can see an increase in the rate of midterm grades being reported for nearly all subgroups Post-SSH, except for the “No Response” group, which had a decrease in reporting rate of 4.4%. we see the biggest increase in the American Indian / Alaska Native population (10.0%), and the smallest increase in the Hispanic population (2.6%).

Across academic colleges, we can see an increase in the rate of midterm grades being reported for nearly all colleges Post-SSH, except for the “Other” group, which had a decrease in reporting rate of over 48%. This is due to the number of individuals included in this group both Pre- and Post-SSH, where the total number of individuals belonging to this group was n = 1591 Pre-SSH, and n = 4 Post-SSH. We see the biggest increase in midterm grade reporting from the College of Health and Human Services (6.7%), and the smallest increase from Merze Tate College (0.7%).

Low Midterm Flag

Table 5

Low Midterm Grade Flags Received over Time

		Low Midterm Grade Flag?		
	n	No	Yes	% Change
All Students	85241	73.9%	26.1%	-
Pre-Post SSH				
Pre-SSH	59939	73.9%	26.1%	-
Post-SSH	25302	74.0%	26.0%	-0.1%
By Year				
2019	16743	73.3%	26.7%	-
2020	15642	71.2%	28.8%	2.1%
2021	14258	70.9%	29.1%	0.3%
2022	13296	81.0%	19.0%	-10.1%
2023	12733	74.1%	25.9%	6.9%
2024	12569	74.0%	26.0%	0.1%

For the overall data sample, low midterm grades were reported around 26% of the time. When examining by Pre- and Post-Implementation of SSH, there was a slight reduction in the rate at which low midterm grades were reported for students, decreasing by 0.1%. When examining the data by year, from 2019 to 2021, we see a gradual increase in the proportion of students receiving low midterm grades. Year 2022 represents an anomaly in the data, where we see a reduction in the proportion of students receiving low midterm grades by around 10%. This could be due to changes in the reporting methods and requirements, and also represents the time when SSH was being transitioned to for the university. It should be noted that a significant portion of the data from 2022 was not reported as missing for the examination of this research question, with only 0.3% being marked as missing. Further investigations on 2022 data will need to be examined to determine a specific cause. From 2023 to 2024, we again see a slight increase in the proportion of students who were receiving low midterm grades. When not considering 2022, we can see that during the other years Pre-SSH (2019-2021), the proportion of students receiving low midterm grades was greater than those Post-SSH (2023-2024), showing that when not accounting for outlying data, there was a reduction in the proportion of students receiving low midterm grades following the implementation of SSH.

Table 6

Low Midterm Grade Flags Received by Student Characteristics Pre- and Post-SSH

	PreSSH		PostSSH		
	No	Yes	No	Yes	% Change
All Students	73.9%	26.1%	74.0%	26.0%	-0.1%
FTIAC Status					
NonFTIAC	74.7%	25.3%	75.2%	24.8%	-0.5%
FTIAC	69.9%	30.1%	69.2%	30.8%	0.7%
Gender					
Female	77.3%	22.7%	77.5%	22.5%	-0.2%
Male	70.5%	29.5%	70.4%	29.6%	0.1%
Race/Ethnicity					
American Indian / Alaska Native	73.1%	26.9%	76.7%	23.3%	-3.6%
Asian	74.0%	26.0%	73.1%	26.9%	0.9%
Black / African American	54.5%	45.5%	52.9%	47.1%	1.6%
Hispanic	69.9%	30.1%	68.9%	31.1%	1.0%
International	77.3%	22.7%	76.0%	24.0%	1.3%
Native Hawaiian / Pacific Islander	68.3%	31.7%	75.0%	25.0%	-6.7%
No Response	72.7%	27.3%	77.0%	23.0%	-4.3%
Two or More Races	69.3%	30.7%	69.1%	30.9%	0.2%
White	77.0%	23.0%	77.3%	22.7%	-0.3%
By College					
Arts & Sciences	71.4%	28.6%	72.7%	27.3%	-1.3%
Aviation	76.7%	23.3%	79.9%	20.1%	-3.2%
Education & Human Dev.	76.0%	24.0%	76.0%	24.0%	0.0%
Engineering & Applied Sciences	68.9%	31.1%	70.3%	29.7%	-1.4%
E.U.P.	73.4%	26.6%	70.2%	29.8%	3.2%
Fine Arts	81.4%	18.6%	82.1%	17.9%	-0.7%
Haworth College of Business	74.4%	25.6%	72.2%	27.8%	2.2%
Health & Human Services	80.5%	19.5%	80.6%	19.4%	-0.1%
Merze Tate College	67.0%	33.0%	53.4%	46.6%	13.6%
Other	54.6%	45.4%	50.0%	50.0%	4.6%

For a comparison of FTIAC vs NonFTIAC students, we see that the proportion of low midterm grades both Pre- and Post-SSH received was greater for FTIAC students versus the NonFTIAC students. We see a slight reduction in the proportion of low midterm grades received for the NonFTIAC students from Pre- to Post-SSH implementation, and a slight increase in the proportion of low midterm grades received for the FTIAC students.

When comparing across genders, we can see a higher proportion of males receiving low midterm grades compared to females across both Pre- and Post-SSH implementation (around 7%). In females, we see a slight reduction in the proportion of low midterm grades received following the implementation of SSH, and for males, we see a slight increase in this proportion.

When comparing across races/ethnicities, we can see a reduction in the proportion of low midterm grades received in four of the subgroups: American Indian / Alaska Native (-3.6%), Native Hawaiian / Other Pacific Islander (-6.7%), No Response (-4.3%), and White (-0.3%). All other groups saw a slight increase in the proportion of students receiving low midterm grades from Pre- to Post-SSH implementation, with the greatest increase being seen in the Black / African American population (1.6%).

When comparing by academic college, we can see a reduction in the proportion of low midterm grades received in five of the subgroups: Arts & Sciences (-1.3%), Aviation (-3.2%), Engineering & Applied Sciences (-1.4%), Fine Arts (-0.7%), and Health & Human Services (-0.1%). There was no change in this proportion for the college of Education & Human Development, and we see the greatest increase in the proportion of students receiving low midterm grades from Merze Tate College (13.6%).

Table 7

Logistics Regression of Low Midterm Grade Flag Pre- and Post-SSH

	β	*SE*	*Wald*	*df*	*Exp(β)*
PreSSH					
Beginning Sem GPA	-0.246	0.006	1608.784	1	0.782
Constant	-0.478	0.016	857.753	1	0.620
PostSSH					
Beginning Sem GPA	-0.229	0.009	624.798	1	0.795
Constant	-0.531	0.024	472.185	1	0.588

**PreSSH:* n = 59939; C & S R^2 = .026; Omnibus χ^2 = 1592.032, $p < .001$.

*Post*SSH:* n = 25302; C & S R^2 = .024; Omnibus χ^2 = 618.943, $p < .001$.

Table 8

Probability of Receiving a Low Midterm Grade Flag by Beginning Semester GPA

	PreSSH		**PostSSH**	
Beginning Semester GPA	Probability of Receiving Low Midterm Grade Flag	% Change	Probability of Receiving Low Midterm Grade Flag	% Change
0.5	35.41%	-2.86%	34.40%	-2.63%
1.0	32.65%	-5.62%	31.86%	-5.16%
1.5	30.01%	-8.27%	29.43%	-7.60%

2.0	27.49%	-10.78%	27.11%	-9.92%
2.5	25.11%	-13.17%	24.91%	-12.12%
3.0	22.86%	-15.41%	22.83%	-14.20%
3.5	20.77%	-17.50%	20.87%	-16.15%
4.0	18.82%	-19.46%	19.05%	-17.98%
0 (Constant)	38.27%	-	37.03%	-

Note. % Change represents the change in probability compared to the constant of receiving a low midterm grade flag.

A series of logistic regressions were performed in order to explore whether we could predict students who receive a low midterm grade flag both Pre- and Post-SSH implementation. The baseline model used a student's beginning semester GPA at the predictor; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model was examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

The model was statistically significant for both PreSSH [χ^2 (1) = 1592.032, $p < .001$], and PostSSH [χ^2 (1) = 1592.032, $p < .001$]. Students beginning of semester WMU GPA explained around 2.5% of the variance in receiving a low midterm grade flag for both models. As a student's beginning semester GPA increases, their odds of receiving a low midterm grade flag decrease. For students with a GPA value of 0, their probability of receiving a low midterm grade flag is around 38% PreSSH, and 37% PostSSH. As GPA increases, their probability of receiving this flag is reduced across both models. Students with a 4.0 GPA have around a 19% probability of receiving a low midterm grade flag both Pre- and Post-SSH. The full range of theses values can be found in Table 8.

In terms of change in predictability PreSSH and PostSSH, the PreSSH model explains more of the variance observed in our dependent variable, however, the difference between the two models in that aspect is not substantial. Additionally, the standard error seen in the PreSSH model is lower compared to that of the PostSSH model, indicating less uncertainty in measurement Pre- compared to Post-SSH.

Model fit was also assessed by a Hosmer and Lemeshow Test. This test was statistically significant for both the Pre-SSH [χ^2 (7) = 5805.576, $p < .001$] and Post-SSH models [χ^2 (7) = 2880.776, $p < .001$], which is indicative of poor fitting models; however, this test is sensitive to the influences of sample size, where the power of the test becomes too high when the sample size is incrementally larger than what is typically recommended for a logistic regression. When this occurs, the Hosmer Lemeshow test will always report a significant, indicating a poor fit. For this reason, it is better to utilize additional methods for assessing model fit.

Because both models were statistically significant, model building using back selection with student characteristics commenced. The final comprehensive PreSSH model was statistically significant, [χ^2 (14) = 3551.933, $p < .001$], and explained around 6% of the variance seen in receiving a low midterm grade flag (C&S R^2 = .058). PreSSH, female students had lower odds of receiving a low midterm grade flag compared to their male counterparts; in addition, students belonging to any academic college, compared to those who belonged to “other” had lower odds of receiving a low midterm grade flag. Finally, many of the minority race/ethnicity populations were not significant predictors of receiving a low midterm grade flag, including American Indian/ Alaska Native, Asian, Native Hawaiian / Other Pacific Islander Two or More Races, and Hispanic individuals. Identifying as Black or African American increased ones odds of receiving a low midterm grade flag, the only variable to do so in this model. Lastly, identifying as White or international also reduced ones odds of receiving a low midterm grade flag.

The final comprehensive PostSSH model was statistically significant, [χ^2 (8) = 1483.126, p < .001], and explained around 6% of the variance seen in receiving a low midterm grade flag (C&S R^2 = .057). PostSSH, female students had lower odds of receiving a low midterm grade flag compared to their male counterparts; in addition, students belonging to the college of Aviation, Fine Arts, or Health & Human Services, compared to those in any other college, had lower odds of receiving a low midterm grade flag. Finally, many of the minority race/ethnicity populations were not significant predictors of receiving a low midterm grade flag, including American Indian/ Alaska Native, Asian, Native Hawaiian / Other Pacific Islander, White, and International students. Identifying as Black or African American, Hispanic, or as Two or more Races increased ones odds of receiving a low midterm grade flag.

Between our Pre- and Post-SSH comprehensive models, the PostSSH model was far more parsimonious than our PreSSH model, and explained a similar amount of variance in our dependent variable. Overall the models themselves were not the best predictors, given the low R^2 values, the incredibly high sample sizes, and violations of the Hosmer Lemeshow test. While the additional variables did not dramatically increase our ability to explain the variance in our dependent variable, it is important to assess student characteristics in order to best identify and serve students to meet their student success needs.

Table 9

Logistics Regression of Low Midterm Grade Flag by Year

	β	***SE***	***Wald***	***df***	***Exp(β)***
2019					
Beginning Sem GPA	-0.211	0.012	323.505	1	0.810
Constant	-0.538	0.031	308.769	1	0.584
2020					
Beginning Sem GPA	-0.257	0.012	481.204	1	0.773
Constant	-0.306	0.032	93.109	1	0.736
2021					
Beginning Sem GPA	-0.288	0.012	532.113	1	0.750
Constant	-0.207	0.034	37.178	1	0.813
2022					

Beginning Sem GPA	-0.265	0.014	355.869	1	0.767
Constant	-0.873	0.036	596.881	1	0.418
2023					
Beginning Sem GPA	-0.214	0.013	272.203	1	0.808
Constant	-0.573	0.034	277.316	1	0.564
2024					
Beginning Sem GPA	-0.244	0.013	355.662	1	0.783
Constant	-0.487	0.035	197.451	1	0.614

**2019:* n = 16743; C & S R^2 = .019; Omnibus χ^2 = 320.033, p < .001.
**2020:* n = 15642; C & S R^2 = .030; Omnibus χ^2 = 478.022, p < .001.
**2021:* n = 14258; C & S R^2 = .037; Omnibus χ^2 = 530.328, p < .001.
**2022:* n = 13296; C & S R^2 = .026; Omnibus χ^2 = 351.425, p < .001.
**2023:* n = 12733; C & S R^2 = .021; Omnibus χ^2 = 269.485, p < .001.
**2024:* n = 12569; C & S R^2 = .028; Omnibus χ^2 = 352.621, p < .001.

In addition to the explorations Pre- and Post-SSH, the data were also explored by academic year to examine whether we could predict students who receive a low midterm grade flag. The baseline model used a student's beginning semester GPA at the predictor. Overall, all of the models by year were statistically significant at the p < .001 level; however, these models did not offer much of a different perspective compared to those completed using the Pre- and Post-SSH time periods. Across the model years, between 2% and 4% of variance in receiving a low midterm flag could be explained by a students beginning semester WMU GPA, where as a student's beginning semester GPA increases, their odds of receiving a low midterm grade flag decrease. Given that these outcomes are not substantially different than the model above, a full write up of their results will be omitted.

Table 10

Logistics Regression of Low Midterm Grade Flag for FTIACs Pre- and Post-SSH

	β	*SE*	*Wald*	*df*	*Exp(β)*
PreSSH					
AP Courses	-0.134	0.023	32.577	1	0.875
HS GPA	-1.597	0.054	889.555	1	0.203
Constant	4.690	0.179	687.360	1	108.806
PostSSH					
AP Courses	-0.118	0.030	15.280	1	0.889
HS GPA	-1.994	0.082	587.712	1	0.136
Constant	6.125	0.277	488.840	1	457.025

**PreSSH:* n = 10085; C & S R^2 = .130; Omnibus χ^2 = 1400.490, p < .001.
*Post*SSH:* n = 4857; C & S R^2 = .172; Omnibus χ^2 = 916.588, p < .001.

Table 11

Probability of Receiving a Low Midterm Grade Flag for FTIACs by High School GPA & AP Course Count

	PreSSH		PostSSH	
	Probability of Receiving Low Midterm Grade Flag	% Change	Probability of Receiving Low Midterm Grade Flag	% Change
AP Courses				
1	99.0%	-0.13%	99.8%	-0.03%
5	98.2%	-0.85%	99.6%	-0.17%
10	96.6%	-2.48%	99.3%	-0.49%
15	93.6%	-5.51%	98.7%	-1.05%
18	90.7%	-8.39%	98.2%	-1.58%
HS GPA				
1.0	95.7%	-3.43%	98.4%	-1.36%
2.0	81.7%	-17.39%	89.4%	-10.34%
3.0	47.5%	-51.61%	53.6%	-46.21%
4.0	15.5%	-83.62%	13.6%	-86.21%
5.0	3.6%	-95.52%	2.1%	-97.69%
0 (Constant)	99.09%	-	99.78%	-

Note. % Change represents the change in probability compared to the constant of receiving a low midterm grade flag.

Logistic regressions were conducted in order to explore whether we could predict students who receive a low midterm grade flag both Pre- and Post-SSH implementation for our FTIAC population. The baseline model used a student's High School GPA and High School AP Course Count as primary predictors; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model will be examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

The model was statistically significant for both PreSSH [χ^2 (1) = 1400.490, $p < .001$], and PostSSH [χ^2 (1) = 916.588, $p < .001$]. PreSSH, FTIAC students High School GPA and number of AP courses explained 13% of the variance seen in our low midterm grade flag variable. This number increased to 17% PostSSH. In terms of change in predictability between PreSSH and PostSSH, the PostSSH model explained substantially more variance (5%); however, the standard error rates seen in the PreSSH model are lower compared to that of the PostSSH model, indicating more uncertainty in measurement Post-SSH.

FTIAC students with lower High School GPAs and Lower AP Course Counts had increased odds of receiving a low midterm grade flag across both Pre- and Post-SSH. Those with no AP courses and a High school GPA of 0.0 had greater than a 99% probability of receiving a low midterm grade flag across both Pre- and Post-SSH models. High School GPA was most influential in predicting whether a student received a low midterm flag, where higher GPAs were associated with a lower probability of receiving a low midterm grade flag. PreSSH, a students AP course count was more influential in predicting their odds of receiving a low midterm grade flag than it was PostSSH. High School GPA was relatively stable in its ability to predict across both models, where students with the highest High School GPA of 5.0 or greater had anywhere from a 2% - 4% probability of receiving a low midterm grade. A sample range of theses values can be found in Table 11.

Model fit was also assessed by a Hosmer and Lemeshow Test. This test was statistically significant for both the Pre-SSH [χ^2 (8) = 30.615, p < .001] and Post-SSH models [χ^2 (8) = 30.130, p < .001], which is indicative of poor fitting models; however, this test is sensitive to the influences of sample size, where the power of the test becomes too high when the sample size is incrementally larger than what is typically recommended for a logistic regression. When this occurs, the Hosmer Lemeshow test will always report a significant, indicating a poor fit. For this reason, it is better to utilize additional methods for assessing model fit.

Student characteristics for these models were also examined to asses their influence on our dependent variable Pre- and Post-SSH. Across both models, we see stability in gender and race in terms of their influence on the dependent variable. In both models, females were less likely to receive a low midterm grade flag compared to their male counterparts. Across both models, white students and international students were also less likely to receive a low midterm grade flag compared to students of other races/ethnicities, while Black or African American students were more likely to receive a low midterm grade flag compared to students of other races/ethnicities. It is important to note that with these variables included, the Pre-SSH model indicated good model fit from the Hosmer and Lemeshow Test, and explained an additional 2% variance in our dependent variable compared to the baseline model (R^2 = .149); however, for the Post-SSH model, the Hosmer and Lemeshow Test did not indicate good model fit, but also explained an additional 2% of variance in our dependent variable compared to the baseline model (R^2 = .197). Given the consistency seen in gender and race effects on our models, these influences should be considered in future examinations of student success outcomes, especially for Black or African American individuals.

Table 12

Logistics Regression of Low Midterm Grade Flag for FTIACs by Year

	β	*SE*	*Wald*	*df*	*Exp(β)*
2019					
AP Courses	-0.188	0.046	16.322	1	0.829
HS GPA	-1.204	0.097	152.668	1	0.300
Constant	3.238	0.322	100.948	1	25.483
2020					
HS GPA	-1.653	0.092	321.831	1	0.191
Constant	5.056	0.316	256.344	1	156.935

2021					
HS GPA	-1.994	0.115	299.039	1	0.136
Constant	6.255	0.393	253.712	1	520.649
2022					
AP Courses	-0.209	0.061	11.619	1	0.812
HS GPA	-1.892	0.122	239.370	1	0.151
Constant	5.397	0.408	174.650	1	220.661
2023					
HS GPA	-2.177	0.114	363.140	1	0.113
Constant	6.657	0.390	291.947	1	778.534
2024					
HS GPA	-2.037	0.108	357.728	1	0.130
Constant	6.243	0.368	287.343	1	514.538

**2019:* n = 2889; C & S R^2 = .092; Omnibus χ^2 = 278.790, p < .001.
**2020:* n = 2563; C & S R^2 = .140; Omnibus χ^2 = 381.268, p < .001.
**2021:* n = 2083; C & S R^2 = .162; Omnibus χ^2 = 368.526, p < .001.
**2022:* n = 2557; C & S R^2 = .139; Omnibus χ^2 = 386.288, p < .001.
**2023:* n = 2423; C & S R^2 = .171; Omnibus χ^2 = 453.876, p < .001.
**2024:* n = 2434; C & S R^2 = .167; Omnibus χ^2 = 445.621, p < .001.

Table 13
Probability of Receiving a Low Midterm Grade Flag for FTIACs by High School GPA & AP Course Count

	Probability of Receiving Low Midterm Grade Flag	% Change
2019		
AP Course: 1	95.5%	-0.75%
AP Course: 18	46.4%	-49.87%
GPA: 1.0	88.4%	-7.79%
GPA: 5.0	5.8%	-90.39%
0 (Constant)	96.22%	-
2020		
GPA: 1.0	96.78%	-2.59%
GPA: 5.0	3.88%	-95.48%
0 (Constant)	99.37%	-
2021		
GPA: 1.0	98.61%	-1.20%
GPA: 5.0	2.38%	-97.43%
0 (Constant)	99.81%	-
2022		

AP Course: 1	99.4%	-0.10%
AP Course: 18	83.7%	-15.86%
GPA: 1.0	97.1%	-2.47%
GPA: 5.0	1.7%	-97.86%
0 (Constant)	99.55%	-
2023		
GPA: 1.0	98.88%	-0.99%
GPA: 5.0	1.44%	-98.43%
0 (Constant)	99.87%	-
2024		
GPA: 1.0	98.53%	-1.27%
GPA: 5.0	1.90%	-97.90%
0 (Constant)	99.81%	-

Note. % Change represents the change in probability compared to the constant of receiving a low midterm grade flag.

Logistic regressions were conducted in order to explore whether we could predict students who receive a low midterm grade flag across academic years 2019 – 2024 for our FTIAC population. The baseline model used a student's High School GPA and High School AP Course Count as primary predictors; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model will be examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

AP course count was only a significant predictor in our models for the 2019 and 2022 academic years. All other years only include High School GPA as their predictor. Adjusting for this, models were statistically significant for all variables in 2019 [χ^2 (2) = 275.790, $p < .001$], and 2022 [χ^2 386.255, $p < .001$]. These two academic years had the lowest R^2 values across all academic years examined, explaining around 9% of the variance for 2019, and around 14% in 2022 for our dependent variable.

For all other academic years, AP course count was dropped from the original models, leaving us with High School GPA as our sole predictor. These models were all statistically significant, [χ^2 (1) = 368.524 – 453.876, $p < .001$]. The variance explained by the models for these academic years were as follows: 2020 (14%), 2021 (16%), 2023 (17%), and 2024 (17%).

FTIAC students with lower High School GPAs and Lower AP Course Counts had increased odds of receiving a low midterm grade flag across all academic years where these variables were a significant predictor. Across all years, those with no AP courses (where applicable) and a High school GPA of 0.0 had a 96% or greater probability of receiving a low midterm grade flag. High School GPA was most influential in predicting whether a student received a low midterm flag, where higher GPAs were associated with a lower probability of receiving a low midterm grade flag. A sample range of theses values can be found in Table 13.

Model fit was also assessed by a Hosmer and Lemeshow Test. This test was not statistically significant for 2019 [χ^2 (8) = 11.749, p = .163], and for 2021 [χ^2 (8) = 12.703, p = .123] indicating good model fit. This model fit test was only statistically significant at the $p < .001$ level for 2023 [χ^2 (8) = 27.760, $p < .001$], indicating poor model fit. Finally, for the remaining academic years these models were statistically significant, but not at the $p < .001$ level [2020, χ^2 (8) = 19.825, p = .011], [2022, χ^2 (8) = 24.376, p = .002], [2024, χ^2 (8) = 18.473, p = .018]. This is still indicative of poor model fit, however, additional tests should be considered to address model fit. Given our sample sizes for these regressions ranged from n = 2083 to 2889, it is not likely that sample size was influential in inflating the power of the test resulting in a significant result.

Overall, it would not appear that the implementation of SSH allowed our models to offer better predictions of students receiving a low midterm grade flag. Two models PreSSH offered good model fit (2019 and 2021), where all other models did not display good model fit. In terms of variance explained in our dependent variable, the models from 2023 and 2024 (our PostSSH academic periods) did offer higher R^2 values at 17%, compared to PreSSH years ranging from 9-16%, indicating more variance explained; however, our standard errors in these models for 2023 and 2024 were also higher indicating more uncertainty in our measurement. Its difficult to claim that the implementation of SSH was influential in predicting our dependent variable across years.

Student characteristics for these models were also examined to asses their influence on our dependent variable across academic years. Across both models, we see stability in gender and race in terms of their influence on the dependent variable. For a majority of the models, Black or African American students were more likely to receive a low midterm grade flag compared to students of other races/ethnicities, except for model years 2019 and 2022. There was no consistency in additional predictors across academic years. The student characteristic variables in each of the models explained an additional 1% - 3% of variance in our dependent variable, and good model fit was indicated by the Hosmer and Lemeshow Test for all model years except for 2022 and 2023.

Low Midterm Count

Table 14

Number of Low Midterm Grades Received Over Time

	0	**1**	**2**	**3**	**4**	**5**
All Students	73.9%	17.2%	6.1%	2.1%	0.6%	.0.1%
Pre-Post SSH						
Pre-SSH	73.9%	17.4%	6.1%	2.0%	0.5%	0.1%
Post-SSH	74.1%	16.7%	6.1%	2.3%	0.7%	0.2%
Change	*+0.2%*	*-0.7%*	-	*+0.3%*	*+0.2%*	*+0.1%*
By Year						
2019	73.3%	18.4%	6.0%	1.8%	0.4%	0.1%

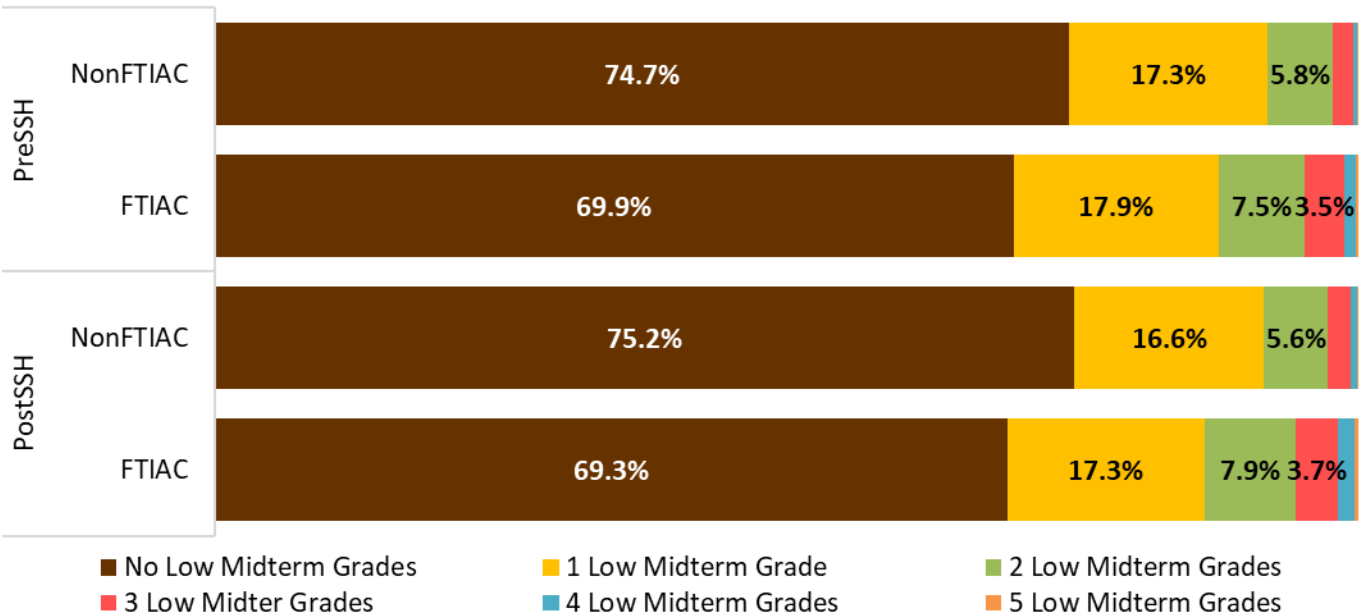
2020	71.2%	17.9%	7.2%	2.7%	0.8%	0.2%
Change	*-2.1%*	*-0.5%*	*+1.2%*	*+0.9%*	*+0.4%*	*+0.1%*
2021	70.9%	18.8%	7.0%	2.6%	0.6%	0.0%
Change	*-0.3%*	*+0.9%*	*-0.2%*	*-0.1%*	*-0.2%*	*-0.2%*
2022	81.0%	14.2%	3.7%	0.9%	0.2%	0.0%
Change	*+10.9%*	*-4.6%*	*-3.3%*	*-1.7%*	*-0.4%*	-
2023	74.2%	16.8%	6.0%	2.2%	0.7%	0.1%
Change	*-6.8%*	*+2.6%*	*+2.3%*	*+1.3%*	*+0.5%*	*+0.1%*
2024	74.0%	16.6%	6.1%	2.5%	0.7%	0.2%
Change	*-0.2%*	*-0.2%*	*+0.1%*	*+0.3%*	-	*+0.1%*

Note. Change value represents the change from prior year in proportion of students receiving that number of low midterm grades.

For students with reported midterm grades, around 74% of student did not receive a low midterm grade from our overall data sample. Looking at the Pre- and Post-SSH implementation periods, the proportion of students receiving low midterm grades remained relatively consistent, and did not fluctuate more than 0.7% for any given group, indicating there was no real impact in the number of students receiving low midterm grades following the implementation of SSH. When broken down by year, we see an increase in the number of students who received no low midterm grades each academic year from 2019 to 2022, which is our pre implementation period. It is important to note that 2022 does display some abnormality compared to all other academic years and periods, and further investigations should be completed to examine the underlying causes to this, as this academic year is when changes in the reporting methods and requirements began to prepare for the implementation of SSH.

Figure 1

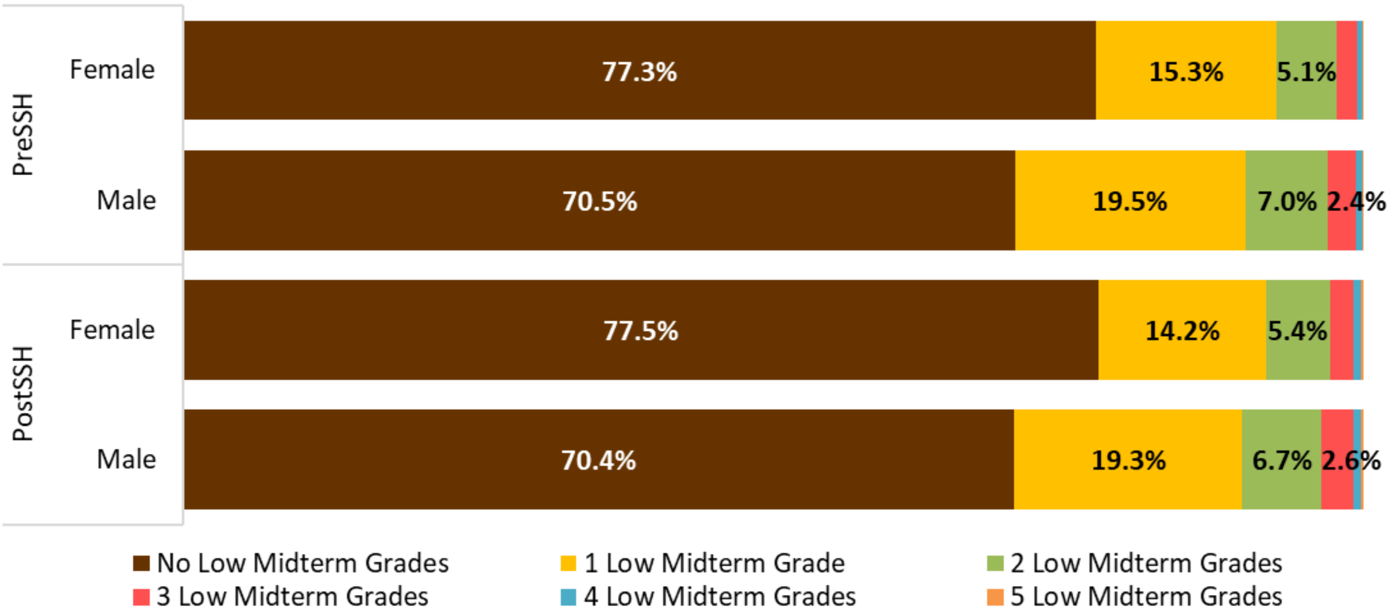
Number of Low Midterm Grades Received for FTIACs Pre- and Post-SSH



For a comparison of FTIAC vs NonFTIAC students, NonFTIAC had a higher rate of receiving no low midterm grades than the FTIAC group; however, these rates amongst the two groups remained relatively consistent both Pre- and Post-SSH implementation. Given this, it is likely that SSH did not influence the rate at which low midterm grades were received by students after its implementation.

Figure 2

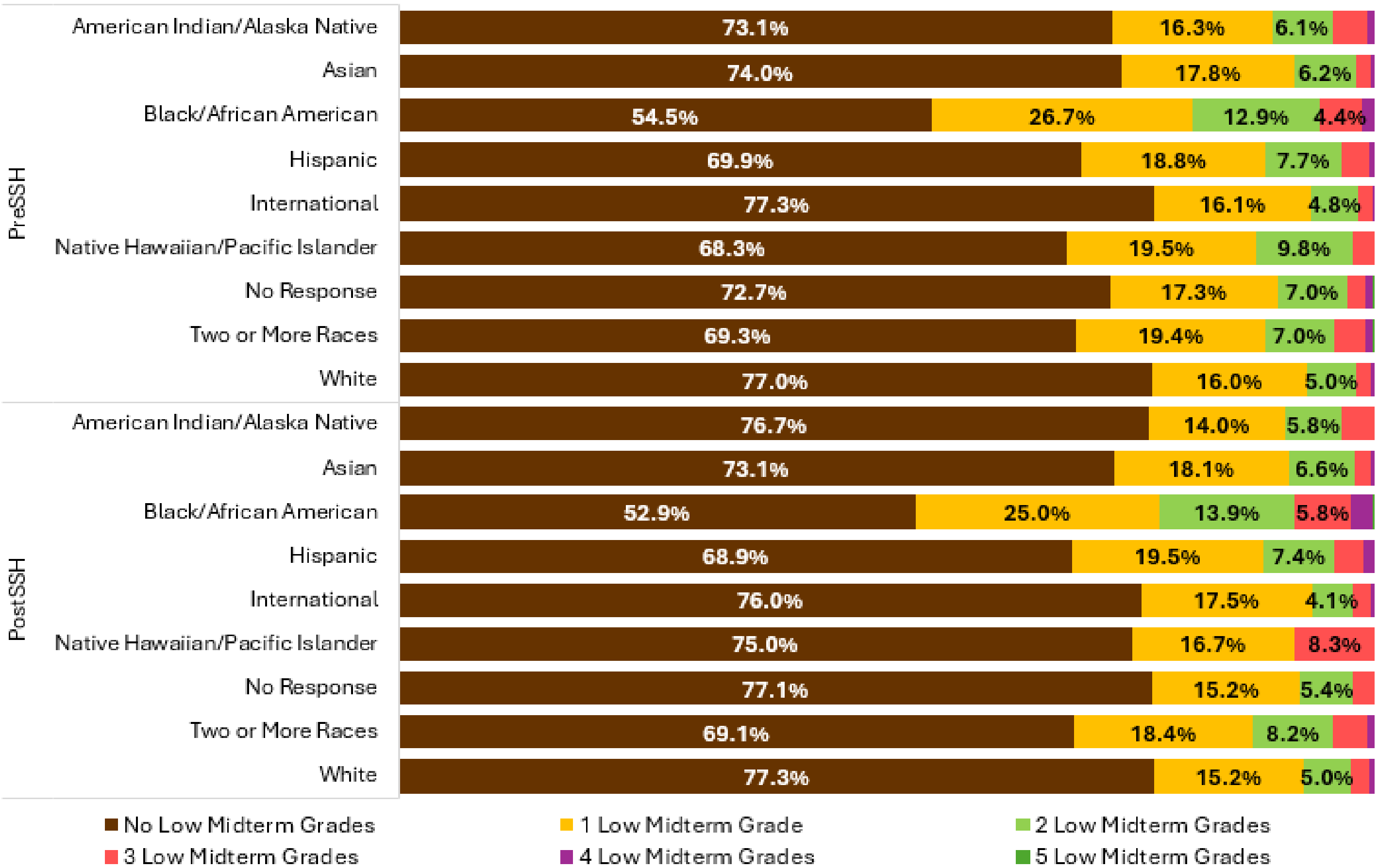
Number of Low Midterm Grades Received by Gender Pre- and Post-SSH



When comparing across genders, we can see that females had a lower rate of low midterm grades received compared to their male counter parts both Pre- and Post-SSH implementation. The rates at which students received low midterm grades remained relatively consistent between the two periods, however, meaning that SSH likely did not impact the number of low midterm grades students receive.

Figure 3

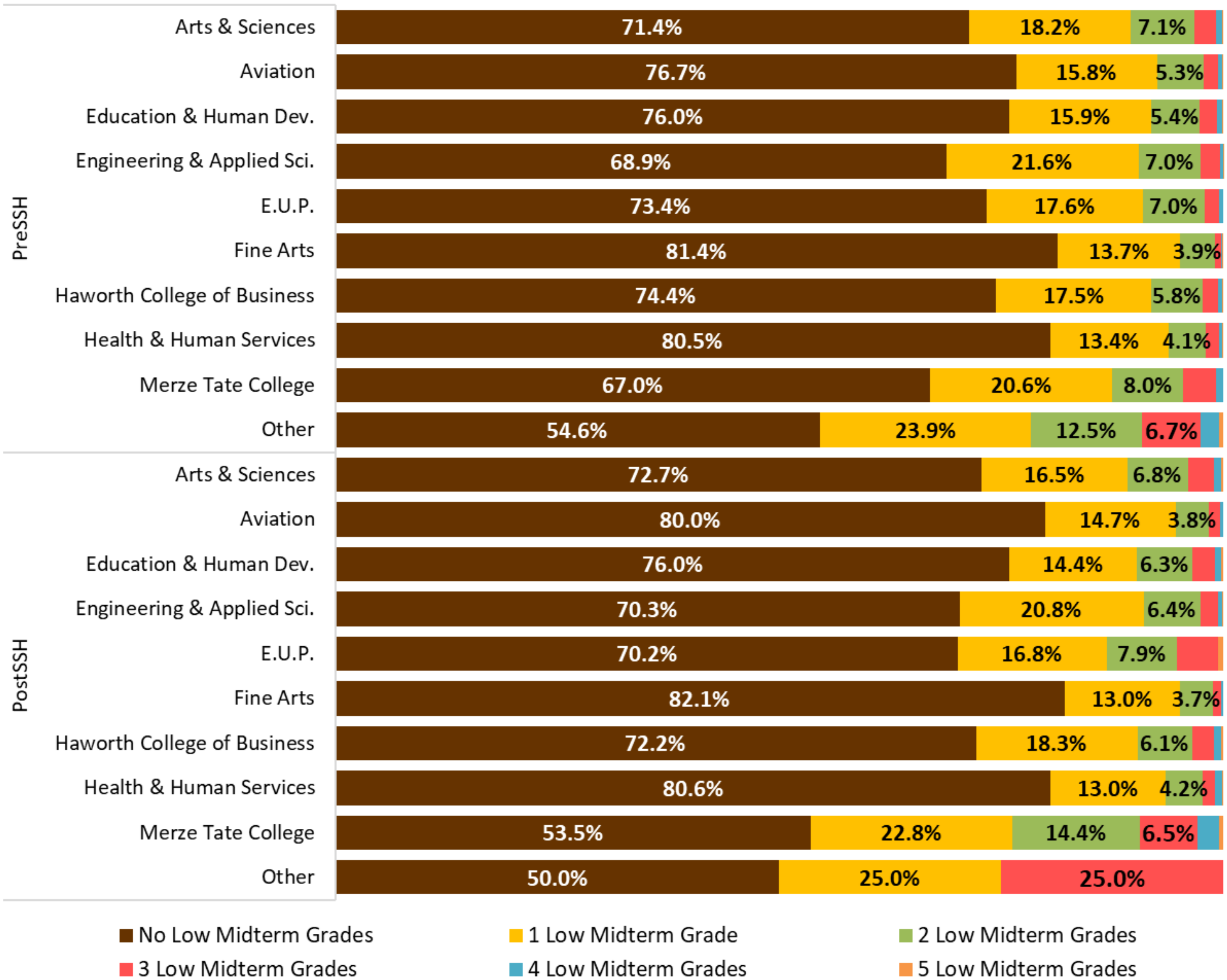
Number of Low Midterm Grades Received by Race/Ethnicity Pre- and Post-SSH



When comparing across races/ethnicities, the number of low midterm grades students received remained relatively stable and consistent, with the exception of our smaller population minorities which saw more students receiving no low midterm grades (American Indian/Alaska Native & Native Hawaiian/Pacific Islander). The group with the greatest proportion of students receiving no low midterm grades was International and White students both Pre- and Post-SSH. Black/African American students consistently had the lowest proportion of students receiving no low midterm grades both Pre- and Post-SSH. Given the stability across the races/ethnicities over time, it is likely that the implementation of SSH did not influence the number of low midterm grades students received.

Figure 4

Number of Low Midterm Grades Received by Academic College Pre- and Post-SSH



The number of low midterm grades received by students was relatively stable both Pre- and Post-SSH implementation, with most academic colleges seeing minor fluctuations. The biggest changes are seen in Merze Tate College and Other, which is likely due to the substantial change in sample size observed within the group between the two periods, where Merze Tate College increased its sample size Post-SSH implementation, and Other drastically decreased Post-SSH implementation. Given the stability amongst the colleges between the academic periods, it is likely that SSH did not influence the number of low midterm grades students received.

Table 15

Linear Regression: Low Midterm Grade Count Pre- and Post-SSH

				95% C.I.	
	B	***SE***	***t***	***LB***	***UB***
PreSSH					
Constant	0.603	0.006	104.724	0.592	0.614
Beginning Semester GPA	-0.092	0.002	-45.124	-0.096	-0.088
PostSSH					
Constant	0.614	0.009	67.829	0.596	0.631
Beginning Semester GPA	-0.092	0.003	-28.761	-0.098	-0.086

**PreSSH:* n = 59939; r = -.181, $p < .001$. Adj. $R^2 = .033$, SEE = .734, $p < .001$.
**PostSSH:* n = 25302; r = -.178, $p < .001$. Adj. $R^2 = .032$, SEE = .774, $p < .001$.

A series of linear regressions were performed to explore the relationship between a students beginning semester GPA and their predicted low midterm grade count Pre- and Post-SSH implementation. The baseline model used a student's beginning semester GPA at the predictor; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model will be examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

The analysis was statistically significant for both Pre-SSH, [$F(1, 59937) = 2036.205$, $p < .001$], and Post-SSH [$F(1, 25300) = 827.169$, $p < .001$], with both models explaining around 3% of the variance in the number of low midterm grades a student receives. The models shows that a students beginning semester GPA was inversely related to the number of low midterm grades they are predicted to receive, meaning that the higher a GPA a student has, the less low midterm grades they are likely to receive. For the Pre-SSH model, students with a beginning semester GPA are predicted to receive, on average, .603 low midterm grades ($M = .38$), where with each additional unit increase in GPA, their expected number of low midterm grades received is reduced by .092. For example, a student with a GPA of 1.0 could be expected to receive .511 low midterm grades, a GPA of 2.0 could be expected to receive .419, and a 4.0 could be expected to receive .235 low midterm grades, on average. For the Post-SSH model, students with a beginning semester GPA are predicted to receive, on average, .614 low midterm grades ($M = .39$), where with each additional unit increase in GPA, their expected number of low midterm grades received is reduced by .092. For example, a student with a GPA of 1.0 could be expected to receive .522 low midterm grades, a GPA of 2.0 could be expected to receive .430, and a 4.0 could be expected to receive .246 low midterm grades, on average.

In terms of model fit, our low R2 values suggest that this model may not best explain changes seen in our dependent variable; additionally, having a high value of our Standard Error of the Estimate (SEE) also indicates that there may be more error in our estimates with lower prediction accuracy. Our F-tests were also both statistically significant both Pre- and Post-SSH, indicating good model fit. Given our extensive sample sizes, most values that are significant at all will be significant at the .001 level; this is considered inflation of significance and can often lead to greater type I errors that result in "false positives," or claiming a statement of effect when there actually was none. Knowing this, model fit and significance should be interpreted cautiously.

In terms of change in predictability PreSSH and PostSSH, both models are relatively equivalent in terms of their predictive ability of our dependent variable. While values do differ slightly, the differences are not substantial.

Because both models were statistically significant, model building using back selection with student characteristics was conducted to examine their influence on our dependent variable. In both models, females had a lower predicted number of low midterm grades compared to their male counterparts. Most academic colleges were significant across both models, where their reference group were students classified as "other." Finally, three racial/ethnic groups stood out across both models: Black/African American, Hispanic, and Two or More Race students. For each of these groups, their predicted low midterm grade count was significantly higher than students of other racial/ethnic backgrounds across both Pre- and Post-SSH models. These findings are consistent with what is usually reported through the university annually for student success outcomes, but should still be considered for future investigations nonetheless.

The final comprehensive models both explained approximately 7% of the variance seen in our dependent variable, but still had sufficiently high SEE values, indicating that there may be more error and less accuracy in our predictive models. Given that the predictive, significance, and fit statistics between both models were quite comparable, it is likely that the implementation of SSH did not have an impact on our dependent variable. While the additional variables did not dramatically increase our ability to explain the variance in our dependent variable, it is important to assess student characteristics in order to best identify and serve students to meet their student success needs.

Given the lack of evidence to suggest an impact from the implementation of SSH on our dependent variable, a by year analysis will not commence with this model.

Table 16

Linear Regression: FTIAC Low Midterm Grade Count Pre- and Post-SSH

	B	***SE***	***t***	***95% CI***
PreSSH				
Constant	2.636	.057	46.039	2.524, 2.748
HS GPA	-.614	.016	-37.967	-.646, -.582
PostSSH				
Constant	3.299	.090	36.697	3.123, 3.476
HS GPA	-.788	.025	-31.202	-.837, -.738

**PreSSH:* n = 10085; $r = -.354$, $p < .001$. Adj. $R^2 = .125$, SEE = .820, $p < .001$.

**PostSSH:* n = 4857; $r = -.409$, $p < .001$. Adj. $R^2 = .167$, SEE = .863, $p < .001$.

Multiple linear regressions were used to examine whether we could predict the number of low midterm grades a student receives Pre- and Post-SSH implementation for our FTIAC population. The baseline model used a student's High School GPA and High School AP Course Count as primary predictors; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model will be examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

For all models, AP course count was not statistically significant and therefore was omitted from the final model. The adjusted models were statistically significant for both PreSSH The analysis was statistically significant for both Pre-SSH, [$F(1, 10083) = 1441.507$, $p < .001$], and Post-SSH [$F(1, 4855) = 973.578$, $p < .001$], with the Pre-SSH model explaining around 13% of the variance in the number of low midterm grades a student receives, and the Post-SSH model explaining around 17% of this variance.

The models shows that a students high school GPA was inversely related to the number of low midterm grades they are predicted to receive, meaning that the higher a GPA a student has, the less low midterm grades they are likely to receive. For the Pre-SSH model, a FTIAC student with a 0.0 high school GPA had, on average, around 2.636 Low midterm grades, where with each additional one unit increase in their HS GPA, the number of low midterm grades they were predicted to have dropped by .614. For example, a student with a GPA of 1.0 could be expected to receive 2.022 low midterm grades, a GPA of 2.0 could be expected to receive 1.408, and a 4.0 could be expected to receive .180 low midterm grades, on average.

For the Post-SSH model, FTIAC students with a high school GPA of 0.0 are predicted to receive, on average, 3.299 low midterm grades ($M = .52$), where with each additional unit increase in GPA, their expected number of low midterm grades received is reduced by .788. For example, a student with a GPA of 1.0 could be expected to receive 2.511 low midterm grades, a GPA of 2.0 could be expected to receive 1.723, and a 4.0 could be expected to receive .147 low midterm grades, on average.

In terms of model fit, our R^2 values suggest that this model may offer a good fit in order to explain changes seen in our dependent variable; additionally, our F-tests were also both statistically significant both Pre- and Post-SSH, indicating good model fit. The models did boast high Standard Error of the Estimate (SEE) values above .800, which indicates that there may be more error in our estimates with lower prediction accuracy. Given our extensive sample sizes, most values that are significant at all will be significant at the .001 level; this is considered inflation of significance and can often lead to greater type I errors that result in "false positives," or claiming a statement of effect when there actually was none. Knowing this, model fit and significance should be interpreted cautiously.

In terms of change in predictability PreSSH and PostSSH, both models are relatively equivalent in terms of their predictive ability of our dependent variable. The PreSSH model does offer a larger F value than our PostSSH model, however, our PostSSH model has a larger R^2 value than our PreSSH model. Both tests have relatively comparable SEE values. Given this information, we can argue that both models offer comparable insight into our dependent variable, and that the implementation of SSH may not have impacted our student success outcomes substantially.

Because both models were statistically significant, model building using back selection with student characteristics was conducted to examine their influence on our dependent variable. In both models, Black/African American students had more low midterm grades on average than a student belonging to any other race/ethnicity. This consistent with what is usually reported through the university annually for student success outcomes, but should still be considered for future investigations nonetheless. The college of Aviation, and the college of Fine Arts were significant across both models, with students belonging to these colleges having less predicted low midterm grades, on average. Across both models, the additional predictor variables explained an additional 2-3% of variance in our dependent variable, indicating good model fit; however, the SEE values were still sufficiently high in both models (>.800), indicating less accurate and more error prone estimates. While the additional variables did not dramatically increase our ability to explain the variance in our dependent variable, it is important to assess student characteristics in order to best identify and serve students to meet their student success needs. Given the lack of evidence to suggest an impact from the implementation of SSH on our dependent variable, a by year analysis will not commence with this model.

Results Section 2: Retention/Persistence

Table 17

Retention/Persistence Over Time

		Retained/Persisted		
	n	No	Yes	% Change
All Students	85469	7.9%	92.1%	-
Pre-Post SSH				
Pre-SSH	60143	8.4%	91.6%	-
Post-SSH	25326	6.7%	93.3%	1.7%
By Year				
2019	16801	7.8%	92.2%	-
2020	15698	9.4%	90.6%	-1.6%
2021	14310	8.8%	91.2%	+0.6%
2022	13334	7.5%	92.5%	+1.3%
2023	12746	7.0%	93.0%	+0.5%
2024	12580	6.4%	93.6%	+0.6%

For the overall data sample, the average rate of retention/persistence was around 92%. When examining by Pre- and Post-Implementation of SSH, we see an increase in the rate of retention/persistence by around 1.7%. When examining by year, except for the change seen from

2019 to 2020, we see a graduate increase in the rate of retention/persistence with each successive academic year.

Table 18

Retention/Persistence by Student Characteristics Pre- and Post-SSH

	PreSSH		PostSSH		
	Not Retained	Retained	Not Retained	Retained	% Change
All Students	8.4%	91.6%	6.7%	93.3%	1.7%
FTIAC Status					
NonFTIAC	8.3%	91.7%	6.7%	93.3%	1.6%
FTIAC	8.8%	91.2%	6.6%	93.4%	2.2%
Gender					
Female	7.6%	92.4%	6.2%	93.8%	1.4%
Male	9.2%	90.8%	7.2%	92.8%	2.0%
Race/Ethnicity					
American Indian / Alaska Native	15.5%	84.5%	8.1%	91.9%	7.4%
Asian	8.1%	91.9%	6.8%	93.2%	1.3%
Black / African American	13.1%	86.9%	12.2%	87.8%	0.9%
Hispanic	10.1%	89.9%	8.7%	91.3%	1.4%
International	5.5%	94.5%	3.8%	96.2%	1.7%
Native Hawaiian / Pacific Islander	19.0%	81.0%	16.7%	83.3%	2.3%
No Response	12.5%	87.5%	7.5%	92.5%	5.0%
Two or More Races	10.9%	89.1%	6.8%	93.2%	4.1%
White	7.5%	92.5%	5.9%	94.1%	1.6%
By College					
Arts & Sciences	9.8%	90.2%	8.1%	91.9%	1.7%
Aviation	8.4%	91.6%	6.5%	93.5%	1.9%
Education & Human Dev.	7.7%	92.3%	5.8%	94.2%	1.9%
Engineering & Applied Sciences	7.2%	92.8%	6.6%	93.4%	0.6%
E.U.P.	17.3%	82.7%	16.8%	83.2%	0.5%
Fine Arts	5.6%	94.4%	4.5%	95.5%	1.1%
Haworth College of Business	7.8%	92.2%	5.3%	94.7%	2.5%
Health & Human Services	7.0%	93.0%	5.7%	94.3%	1.3%
Merze Tate College	15.7%	84.3%	14.0%	86.0%	1.7%
Other	15.7%	84.3%	25.0%	75.0%	-9.3%

For a comparison of FTIAC vs NonFTIAC students, we see that retention/persistence is relatively comparable among the two groups, with NonFTIAC students having slightly higher retention PreSSH, and FTIAC students having slightly higher retention PostSSH; we do, however, see a greater % change in retention with the FTIAC group compared to the NonFTIAC group.

When comparing across genders, females had a higher rate of retention than males both Pre- and Post-SSH; males had a greater % change in their rate of retention than females from Pre- to Post-SSH implementation.

When comparing across races/ethnicities, individuals belonging Asian, International, and White populations all had higher rates of retention Pre-SSH compared to other races/ethnicities, with the largest retention rate both Pre- and Post-SSH being seen in the international population, and the lowest being seen in the Native Hawaiian / Pacific Islander population. The American Indian / Alaska Native population saw the greatest increase in retention rates between Pre- and Post-SSH implementation, and the Black / African American population had the lowest % change in retention.

Across academic colleges, those in nontraditional academic colleges including EUP, Merze Tate, and Other all had the lowest rates of retention both Pre- and Post-SSH. The highest retention rates were seen in the college of Fine Arts across both periods, and our greatest increase in retention rate was seen in the Haworth College of Business. Students in the "Other" group showed a decrease in retention rate from Pre- to Post-SSH implementation, but this is likely due to drastic changes observed in sample size between the two periods, and is therefor an outlier in the data.

Table 19

Retention/Persistence by Low Midterm Flag Over Time

	No Low Midterm Flag		**Low Midterm Flag Received**		
	Not Retained	Retained	Not Retained	Retained	% Difference
All Students	5.2%	94.8%	15.0%	85.0%	-9.8%
Pre-Post SSH					
Pre-SSH	5.7%	94.3%	15.6%	84.4%	-9.9%
Post-SSH	4.2%	95.8%	13.5%	86.5%	-9.3%
By Year					
2019	5.3%	94.7%	14.2%	85.8%	-8.9%
2020	6.2%	93.8%	16.9%	83.1%	-10.7%
2021	5.9%	94.1%	15.3%	84.7%	-9.4%
2022	5.3%	94.7%	16.2%	83.8%	-10.9%
2023	4.5%	95.5%	13.9%	86.1%	-9.4%
2024	3.9%	96.1%	13.2%	86.8%	-9.3%

Students across all time periods who had a low midterm grade flag had around 10% lower rates of retention compared to students who did not have a low midterm grade flag. From

Pre- to Post-SSH implementation, we see this gap closed slightly, with more students from both groups being retained following implementation. Across academic years, we see a general upward trend in retention across all years for students with and without a low midterm grade flag, with the highest retention rates being seen in 2024, and the lowest being seen in 2020.

Table 20

Logistic Regression: Retention/Persistence Pre- and Post-SSH

	β	***SE***	***Wald***	***df***	***Exp(β)***
PreSSH					
Low Midterm Count	-0.665	0.015	2047.807	1	0.515
Constant	2.781	0.019	21962.090	1	16.13
PostSSH					
Low Midterm Count	-0.640	0.023	802.645	1	0.527
Constant	3.032	0.032	8971.793	1	20.731

**PreSSH:* n = 59939; C & S $R^2 = .030$; Omnibus $\chi^2 = 1817.387$, $p < .001$.

*Post*SSH:* n = 25302; C & S $R^2 = .027$; Omnibus $\chi^2 = 695.001$, $p < .001$.

Table 21

Probability of Receiving a Low Midterm Grade Flag by Beginning Semester GPA

	PreSSH		**PostSSH**	
Low Midterm Grade Count	Probability of Retaining	% Change	Probability of Retaining	% Change
1	89.24%	-4.92%	91.62%	-3.78%
2	81.02%	-13.15%	85.22%	-10.18%
3	68.70%	-25.47%	75.25%	-20.15%
4	53.02%	-41.14%	61.59%	-33.81%
5	36.73%	-57.44%	45.81%	-49.59%
6	22.99%	-71.18%	30.83%	-64.57%
7	13.31%	-80.86%	19.03%	-76.37%
8	7.32%	-86.85%	11.03%	-84.37%
0 (Constant)	94.16%	-	95.40%	-

Note. % Change represents the change in probability compared to the constant of receiving a low midterm grade flag.

A series of logistic regressions were performed in order to explore whether we could predict retention using the number of low midterm grades a student receives both Pre- and Post-SSH implementation. The baseline model used a student's low midterm grade count at the predictor; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model was examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

The model was statistically significant for both PreSSH [χ^2 (1) = 1817.387, p < .001], and PostSSH [χ^2 (1) = 695.001, p < .001]. Students low midterm grade count explained around 3% of the variance in retention for both models. As a low midterm grade count increases, their odds of retaining decrease. For students with no low midterm grades, their probability of retaining is around 94.2% PreSSH, and 95.4% PostSSH. Those with the maximum amount of 8 low midterm grades had only a 7.3% predicted probability of retaining PreSSH, and an 11.0% PostSSH. The full range of theses values can be found in Table 21.

PreSSH and PostSSH, the PreSSH model explains slightly more of the variance observed in our dependent variable, however, the difference between the two models in that aspect is not substantial. Additionally, the standard error seen in the PreSSH model is lower compared to that of the PostSSH model, indicating less uncertainty in measurement Pre- compared to Post-SSH.

Model fit was also assessed by a Hosmer and Lemeshow Test. This test was statistically significant for both the Pre-SSH [χ^2 (1) = 7.973, p = .005] and Post-SSH models [χ^2 (1) = 21.826, p < .001], which is indicative of poor fitting models; however, this test is sensitive to the influences of sample size, where the power of the test becomes too high when the sample size is incrementally larger than what is typically recommended for a logistic regression. When this occurs, the Hosmer Lemeshow test will always report a significant, indicating a poor fit. For this reason, it is better to utilize additional methods for assessing model fit.

Because both models were statistically significant, model building using back selection with student characteristics commenced. The final comprehensive PreSSH model was statistically significant, [χ^2 (12) = 2147.511, p < .001], and explained around 3.5% of the variance seen in retention (C&S R^2 = .035), which was only a 0.5% increase in variance explained. In this model, having a low midterm grade, and belonging to the academic college EUP were both negatively associated with retention, decreasing ones odds of retention compared to those from other academic colleges or with no low midterm grades. For race/ethnicity, white and international identifying students had higher odds of retaining compared to all other students, and females had higher odds of retaining than males. Students belonging to any other academic college also had higher odds of retention compared to those who belonged to EUP, Merze Tate, and "Other."

The final comprehensive PostSSH model was statistically significant, [χ^2 (6) = 785.157, p < .001], and explained around 3% of the variance seen in retention (C&S R^2 = .031), which was only a 0.4% increase in variance explained. In this model, having a low midterm grade, and identifying as Black/African American or Hispanic were all negatively associated with retention, where those belonging to any of these groups had lower odds of retention compared to students with no low midterm grades or students of any other racial/ethnic group. Students from the college of Education & Human Development, Fine Arts, or Haworth College of business all had higher odds of retention compared to students belonging to any other academic college PostSSH.

Between our Pre- and Post-SSH comprehensive models, the PostSSH model was far more parsimonious than our PreSSH model, and explained a similar amount of variance in our dependent variable. Overall the models themselves were not the best predictors, given the low R^2

values, the incredibly high sample sizes, and violations of the Hosmer Lemeshow test. While the additional variables did not dramatically increase our ability to explain the variance in our dependent variable, it is important to assess student characteristics in order to best identify and serve students to meet their student success needs. Given the lack of evidence to suggest an impact from the implementation of SSH on our dependent variable, a by year analysis will not commence with this model.

Table 22

Logistic Regression: FTIAC Retention/Persistence Pre- and Post-SSH

	β	***SE***	***Wald***	***df***	***Exp(β)***
PreSSH					
Low Midterm Count	-0.688	0.031	496.667	1	0.502
AP Course Count	0.293	0.048	37.273	1	1.340
Constant	2.752	0.051	2968.423	1	15.681
PostSSH					
Low Midterm Count	-0.600	0.044	184.303	1	0.549
Constant	3.135	0.077	1650.033	1	22.995

**PreSSH:* n = 10085; C & S R^2 = .057; Omnibus χ^2 = 591.361, p < .001.

*Post*SSH:* n = 4857; C & S R^2 = .033; Omnibus χ^2 = 163.586, p < .001.

Table 23

Probability of Retention for FTIACs

	PreSSH		**PostSSH**	
Low Midterm Grade Count	Probability of Retaining	% Change	Probability of Retaining	% Change
1	88.7%	-5.27%	92.7%	-3.18%
2	79.8%	-14.17%	87.4%	-8.45%
3	66.6%	-27.45%	79.2%	-16.66%
4	50.0%	-44.00%	67.6%	-28.24%
5	33.4%	-60.55%	53.4%	-42.46%
6	20.2%	-73.84%	38.6%	-57.25%
7	11.3%	-82.74%	25.6%	-70.20%
8	6.0%	-88.01%	15.9%	-79.92%
AP Courses Count				
1	95.5%	1.45%		
2	96.6%	2.57%		
5	98.5%	4.54%		
10	99.7%	5.66%		
15	99.9%	5.92%		

0 (Constant)	94.00%	-	95.83%	-

Note. % Change represents the change in probability compared to the constant of receiving a low midterm grade flag.

Logistic regressions were conducted in order to explore whether we could predict retention in FTIAC students Pre- and Post-SSH implementation. The baseline model used a student's Low midterm grade count, High School GPA and AP Course Count as primary predictors; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model will be examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

High school GPA was not a significant predictor of retention in FTIACs for either of our models, and was dropped from the analysis. AP course count was only significant in the PreSSH model, and was dropped from the PostSSH model.

Given these adjustments, the resulting models were statistically significant for both PreSSH [χ^2 (2) = 591.361, $p < .001$], and PostSSH [χ^2 (1) = 163.586, $p < .001$]. PreSSH, FTIAC students Low midterm grade count and number AP courses explained 6% of the variance seen in retention. Low midterm grade count explained around 3% of the variance in retention for the PostSSH model. In terms of change in predictability between PreSSH and PostSSH, the PreSSH model explained more variance than the Post SSH model, and had smaller standard error values compared to the PostSSH model, indicating more uncertainty in measurement Post-SSH. Model fit was also assessed by a Hosmer and Lemeshow Test. This test was statistically significant for both the Pre-SSH [χ^2 (4) = 11.757, p = .019] and Post-SSH models [χ^2 (1) = 6.569, p = .010], which is indicative of poor fitting models; however, this test is sensitive to the influences of sample size, where the power of the test becomes too high when the sample size is incrementally larger than what is typically recommended for a logistic regression. When this occurs, the Hosmer Lemeshow test will always report a significant, indicating a poor fit. For this reason, it is better to utilize additional methods for assessing model fit.

PreSSH, FTIAC students with less low midterm grades and greater AP Course Counts had increased odds of retention, compared to those with more low midterm grades and no AP courses. Those with no AP courses no low midterm grades had a 94% probability of retaining; those with no low midterm grades and 15 AP courses had a 99.9% probability of retaining; and finally, those with 8 low midterm grades and no AP courses had a 6% probability of retaining. A sample range of theses values can be found in Table 23.

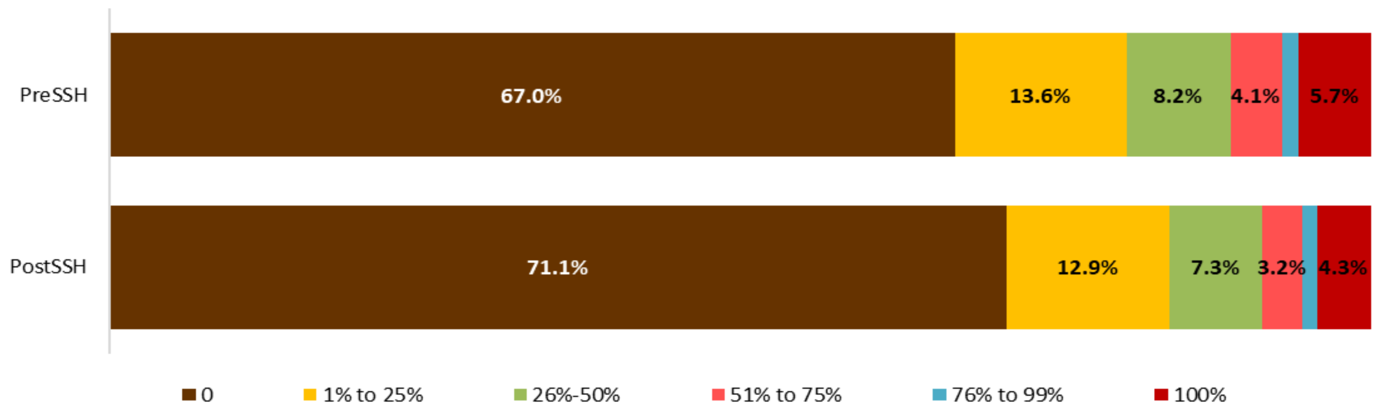
PostSSH, FTIAC students with less low midterm grades had greater odds of retention compared to those with more low midterm grades. A student with no low midterm grades had a 96% probability of retaining, while those with 8 low midterm grades had a 16% probability of retaining. A sample range of theses values can be found in Table 23.

Student characteristics for these models were also examined to asses their influence on our dependent variable Pre- and Post-SSH. For the PreSSH model, only students from the College of Arts and Sciences, and White identifying students were significant, in addition to our baseline model. Those from the college of Arts and Sciences had lower odds of retention compared to any other academic college, and white students had higher odds of retention, compared to students from any other race or ethnicity. Our C&S $R^2 = .060$, showing only a .003 increase in variance explained in retention with the addition of these variables. For the PostSSH model, no student characteristics were significant predictors in addition to our baseline model. Given the

Results Section 3: Proportion of Courses not Passed

Figure 5

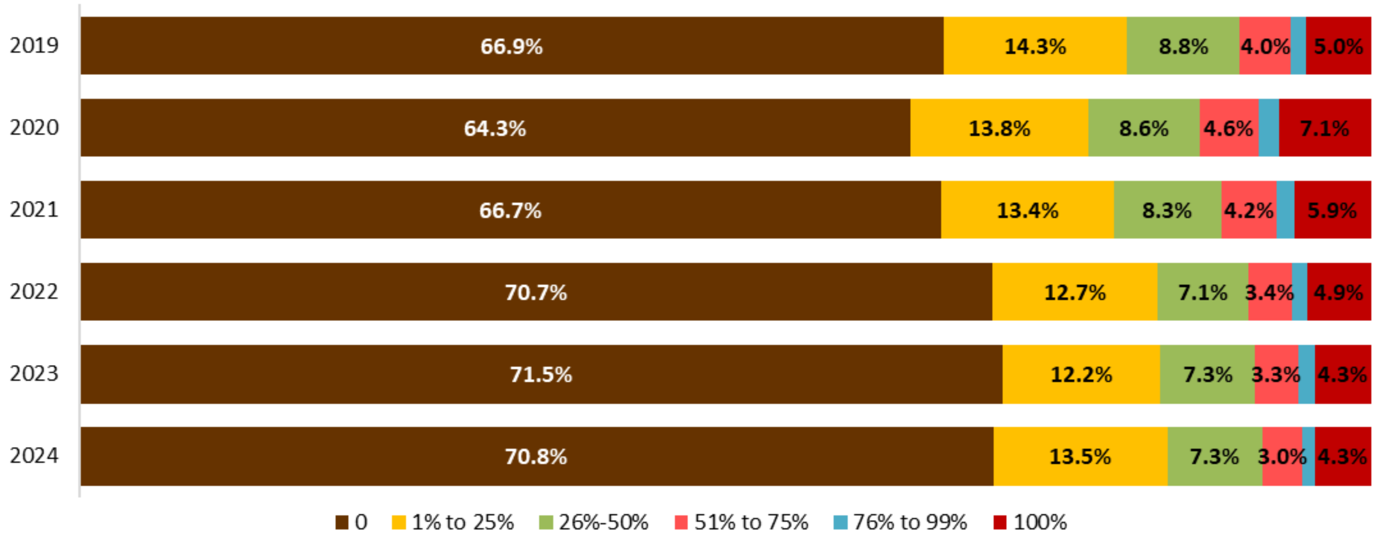
Proportion of Courses not Passed Pre- and Post-SSH



From Pre- to Post-SSH, we see an increase in the proportion of students with no failed courses, and a decrease in the number of students who failed all courses. PreSSH, the average proportion value for any given student was 0.131. PostSSH, the average proportion value was .159. The median proportion value for both Pre- and Post-SSH was .00, which is more informative of our sample, as it removes the influence of outliers or significant data points. Given the extensive sample size in PreSSH (n = 60033) compared to PostSSH (n = 25311), caution should be taken when comparing average proportions across time, as these sample sizes could influence their value given the limited range of values it can take.

Figure 6

Proportion of Courses not Passed by Academic Year



From 2019 to 2024, we see a trended increase in the proportion of students with no failed courses, and a trended decrease in the proportion of students who failed all courses. The average proportion values for each academic year are as follows: 2019 = .154, 2020 = .180, 2021 = .163, 2022 = .138, 2023 = .133, and 2024 = .131. For all academic years, the median proportion value was .00. Sample sizes across these years was reduced with each additional academic year, where the sample in 2019 was n = 16764, and by 2024 was n = 12573. Caution should be taken when interpreting average proportion values due this consideration.

Results Section 4: End of Semester GPA

Table 24

End of Semester GPA Over Time

		End of Semester GPA			
	n	0.00 to 1.00	1.01 to 2.00	2.01 to 3.00	3.01 to 4.00
All Students	85469	7.6%	7.3%	22.3%	62.8%
Pre-Post SSH					
Pre-SSH	60143	8.1%	7.7%	23.1%	61.0%
Post-SSH	25326	6.4%	6.3%	20.4%	66.9%
By Year					
2019	16801	7.3%	8.6%	26.8%	57.3%
2020	15698	9.0%	7.2%	22.5%	61.3%
2021	14310	8.7%	8.1%	22.0%	61.2%
2022	13334	7.3%	6.8%	20.5%	65.4%

2023	12746	6.7%	6.6%	21.0%	65.7%
2024	12580	6.0%	6.1%	19.8%	68.2%

From Pre- and Post-SSH, we see a clear increase in students who are earning high end of semester GPA marks, especially those who are earning marks in the 3.01 to 4.00 range. Additionally, we see a decrease in the number of students who are earning marks in the 0.00 to 1.00 range. PreSSH, the average end of semester GPA was a 2.97, which increased to a 3.10 PostSSH, indicating that there is a change in end of semester GPA following the implementation of SSH.

By academic year, we see a similar trend to that observed Pre- and Post-SSH, where there is a clear increase in students who are earning high end of semester GPA marks; however, this is only observed in the 3.01 to 4.00 group, and we see a reductio in the number of students earning marks in the 2.01 to 3.00 group over time. By academic year, the average end of semester GPA marks were as follows: 2019 = 2.93, 2020 = 2.96, 2021 = 2.96, 2022 = 3.05, 2023 = 3.08, and 2024 = 3.13. By year, we again see this steady increase in average end of semester GPA. This change was already in progress prior to the implementation of SSH, which may suggest that SSH itself was not influential in this change.

Table 25

Linear Regression: End of Semester GPA Pre- and Post-SSH

				95% C.I.	
	B	***SE***	***t***	***LB***	***UP***
PreSSH					
Constant	3.280	0.004	821.285	3.272	3.288
Low Midterm Count	-0.781	0.005	-163.760	-0.790	-0.771
PostSSH					
Constant	3.402	0.006	603.594	3.391	3.413
Low Midterm Count	-0.739	0.006	-115.366	-0.752	-0.727

**PreSSH:* n = 59939; r = -.556, $p < .001$. Adj. $R^2 = .309$, SEE = .871, $p < .001$.

**PostSSH:* n = 25302; r = -.587, $p < .001$. Adj. $R^2 = .345$, SEE = .801, $p < .001$.

A series of linear regressions were performed to explore the relationship between a students low midterm grade count and their predicted end of semester GPA Pre- and Post-SSH implementation. The baseline model used a student's low midterm grade count at the predictor; if this baseline model was statistically significant at the $p < .001$ level, a more comprehensive model will be examined using student characteristics as additional predictors, including academic college, gender, and race/ethnicity.

The analysis was statistically significant for both Pre-SSH, [$F(1, 59937) = 26817.445$, $p < .001$], and Post-SSH [$F(1, 25300) = 13309.218$, $p < .001$], with the PreSSH model explaining around 31% and PostSSH model explaining around 35% of the variance in end of semester GPA.

The models shows that a students end of semester GPA was inversely related to the number of low midterm grades they receive, meaning that the more low midterm grades they receive, the lower their end of semester GPA is predicted to be.

For the Pre-SSH model, students with no low midterm grades had a 3.28 end of semester GPA, on average. With each additional low midterm grade a student received, this GPA value is reduced by .781. For example, a student with one low midterm grade would be predicted to have a 2.499 GPA, whereas a student with 3 low midterm grades would be predicted to have a 0.937 GPA.

For the Post-SSH model, students with no low midterm grades had a 3.402 end of semester GPA, on average. With each additional low midterm grade a student received, this GPA value is reduced by .739. For example, a student with one low midterm grade would be predicted to have a 2.67 GPA, whereas a student with 3 low midterm grades would be predicted to have a 1.188 GPA.

In terms of model fit, our large R^2 values suggest that this model may explain changes in our dependent variable well; however, in addition to this, we also see very high Standard Error of the Estimate (SEE) values, indicating that there may be more error in our estimates with lower prediction accuracy. Our F-tests were also both statistically significant both Pre- and Post-SSH, typically indicating good model fit, however, theses values are also inflated. Given these extensive sample sizes, most values that are significant at all will be significant at the .001 level; this is considered inflation of significance and can often lead to greater type I errors that result in "false positives," or claiming a statement of effect when there actually was none. Knowing this, model fit and significance should be interpreted cautiously.

In terms of change in predictability PreSSH and PostSSH, both models are relatively equivalent in terms of their predictive ability of our dependent variable. While values do differ slightly, the differences are not substantial.

In addition to the suspicious about model fit, it is also likely that this model is experiencing the influences of multicollinearity, or two variables being used in a model that have very high correlations. Given the lack of evidence to suggest an impact from the implementation of SSH on our dependent variable, and the likely violation of assumptions with our model, the student characteristic analysis and the by year analysis will not commence with this model.

References

Flynn, E. (2023, March 14). Unprecedented cross-campus collaboration leads to streamlines student support. *WMU News*. https://wmich.edu/news/2023/03/70934

Western Michigan University. (n.d.). *Navigator network: Student success hub.* https://wmich.edu/navigator/student-success-hub

Appendix A

Recoded Variables

Original Variable & Level	New Variable	Measurement
COLLEGE: Arts & Sciences	ArtSci	Binary [Yes / No]
COLLEGE: Aviation	Aviation	Binary [Yes / No]
COLLEGE: Education & Human Development	EduHumD	Binary [Yes / No]
COLLEGE: Engineering	Engineer	Binary [Yes / No]
COLLEGE: Fine Arts	FineArts	Binary [Yes / No]
COLLEGE: Haworth College of Business	Business	Binary [Yes / No]
COLLEGE: Health and Human Services	HHS	Binary [Yes / No]
COLLEGE: Merze Tate	MerzeTate	Binary [Yes / No]
COLLEGE: Extended University Programs	EUP	Binary [Yes / No]
COLLEGE: Other	Other	Binary [Yes / No]
Gender	Female	Binary [Yes / No]
RACE_ETHNICITY: White	White	Binary [Yes / No]
RACE_ETHNICITY: Native American / Alaska Native	Indig	Binary [Yes / No]
RACE_ETHNICITY: Black / African American	Black	Binary [Yes / No]
RACE_ETHNICITY: Hispanic	Hispanic	Binary [Yes / No]
RACE_ETHNICITY: International	International	Binary [Yes / No]
RACE_ETHNICITY: Two or More Races	BiRacial	Binary [Yes / No]
RACE_ETHNICITY: Asian	Asian	Binary [Yes / No]
RACE_ETHNICITY: Native Hawaiian / Pacific Islander	HativeH	Binary [Yes / No]
RACE_ETHNICITY: No Response	NoResonse	Binary [Yes / No]
PrePostSSH	PostSSH	Binary [Yes / No]
HS_GPA	Imp_Transf_HS_GPA	Ratio

Appendix B
Correlation Matric for Quantitative Variables

Correlations

		LOW_MIDTERM_GRADE_COUNT	AP_COURSE_COUNT	BEG_SEM_GPA	ENDS_SEM_GPA	END_SEM_ACCUM_GPA	Imp_Transf_HS_GPA	COURSES_ATTEMPTED	PASSED_COURSES_COUNT	FAILED_COURSES_COUNT
AP_COURSE_COUNT	Pearson Correlation	-.095**								
	Sig. (2-tailed)	<.001								
	N	85241								
BEG_SEM_GPA	Pearson Correlation	-.180**	.064**							
	Sig. (2-tailed)	<.001	<.001							
	N	85241	85469							
ENDS_SEM_GPA	Pearson Correlation	-.563**	.133**	.194**						
	Sig. (2-tailed)	<.001	<.001	<.001						
	N	85241	85469	85469						
END_SEM_ACCUM_GPA	Pearson Correlation	-.565**	.184**	.328**	.818**					
	Sig. (2-tailed)	<.001	<.001	<.001	<.001					
	N	83907	84032	84032	84032					
Imp_Transf_HS_GPA	Pearson Correlation	-.211**	.352**	.110**	.276**	.368**				
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001				
	N	85232	85460	85460	85460	84023				
COURSES_ATTEMPTED	Pearson Correlation	.067**	.112**	-.119**	.136**	.083**	.140**			
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001			
	N	85241	85241	85241	85241	83907	85232			
PASSED_COURSES_COUNT	Pearson Correlation	-.380**	.151**	.055**	.669**	.557**	.254**	.715**		
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001		
	N	85241	85344	85344	85344	83907	85335	85241		
FAILED_COURSES_COUNT	Pearson Correlation	.616**	-.093**	-.207**	-.806**	-.719**	-.211**	.058**	-.656**	
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	85241	85241	85241	85241	83907	85232	85241	85241	
PROPORTION_COURSES_NOT_PASSED	Pearson Correlation	.564**	-.095**	-.183**	-.862**	-.717**	-.217**	-.099**	-.732**	.936**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	85241	85344	85344	85344	83907	85335	85241	85344	85241

**. Correlation is significant at the 0.01 level (2-tailed).