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Analyzing Learning Assistant influence on STEM student success using logistic and hierarchical regression

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ABSTRACT

The increasing demand for a robust science, technology, engineering, and mathematics (STEM) workforce highlights the need to understand factors that enhance student success in STEM fields. Despite significant need for STEM-qualified individuals, less than half of students initially expressing STEM interest upon college entry graduate with a STEM degree, dropping lower for underrepresented students. The Learning Assistant (LA) program, implemented at colleges around the world, involves students (LAs) aiding their peers through evidence based collaborative activities in STEM courses. It has been well documented that LAs are associated with short-term student success (lower course failure rates) and long-term student success (higher graduation rates). In this study we investigate the impact of the LA program on student success in introductory STEM courses. We analyzed over 10 years of student data, focusing on DFW (D, F, or withdraw) and six-year graduation rates. Using logistic regression and hierarchical linear models, we assessed the influence of LA support on student outcomes, with particular attention to marginalized demographics and repeated LA exposure. We show that LA-supported students in introductory physics courses experienced a 7% decrease in DFW rates. Notably, underrepresented students saw a 10% reduction in DFW rates. Additionally, repeated LA exposure in physics courses provided greater benefits for DFW rates compared to single-course exposure. This research underscores the importance of LA programs in improving STEM education outcomes, notably for underrepresented students.

Keywords: Learning Assistant, student success, logistic regression, hierarchical model, DFW rate, graduation rate

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INTRODUCTION

In an era of rapid technological advancements, the demand for a robust science, technology, engineering, and mathematics (STEM) workforce is critical for driving innovation in the US (National Science Foundation, 2023). A study conducted in 2020 by the Center for Strategic and International Studies highlighted the economic advantages of pursuing a STEM career (Athanasia & Cota, 2022). Even with the incentive of generally competitive salaries, as of this writing, there is a shortage of STEM graduates compared to the number of current STEM jobs (Boggs et al., 2022). The recent CSIS study also found that STEM fields account for nearly 30% of current US job openings in many major metropolitan areas, yet only 11% of the US population holds a STEM degree on average (Athanasia & Cota, 2022). Furthermore, this scarcity not only jeopardizes the competitiveness of US industries but also has the potential to prompt companies to offshore operations or intensify automation efforts in production (Athanasia & Cota, 2022). In order to meet these workforce needs, it is important to understand factors that contribute to student success in STEM education.

It has been well-documented that underrepresented minority students, as well as women and first-generation (FG) students in STEM majors, face additional barriers to success when pursuing STEM degrees in the US (Estrada et al., 2016; Van Dusen & Nissen, 2020). In the US, fewer than 40% of students who initially express an interest in STEM successfully obtain a STEM degree, dropping to 20% for underrepresented students (Freeman et al., 2014). This disparity is particularly acute among typically underrepresented minority groups, including African American, Latino American, and Native American (AALANA) students (Grossman & Porche, 2014). Gender barriers within STEM fields further compound these challenges. Despite increases in women attaining degrees in biology and social and behavioral sciences, studies have found disproportionately higher representation of men in fields such as physics, engineering, mathematics, and computer science (Grossman & Porche, 2014; Swafford & Anderson, 2020). Being an FG student is also regarded as a barrier to success. An FG college student is typically defined as someone whose parents have not obtained a bachelor's degree or higher before the student has enrolled in college (FirstGen Forward, 2024). On the other hand, continuing-generation (CG) college students come from families where at least one parent has completed a bachelor's degree or higher. FG students account for 15.9% of incoming college freshmen on

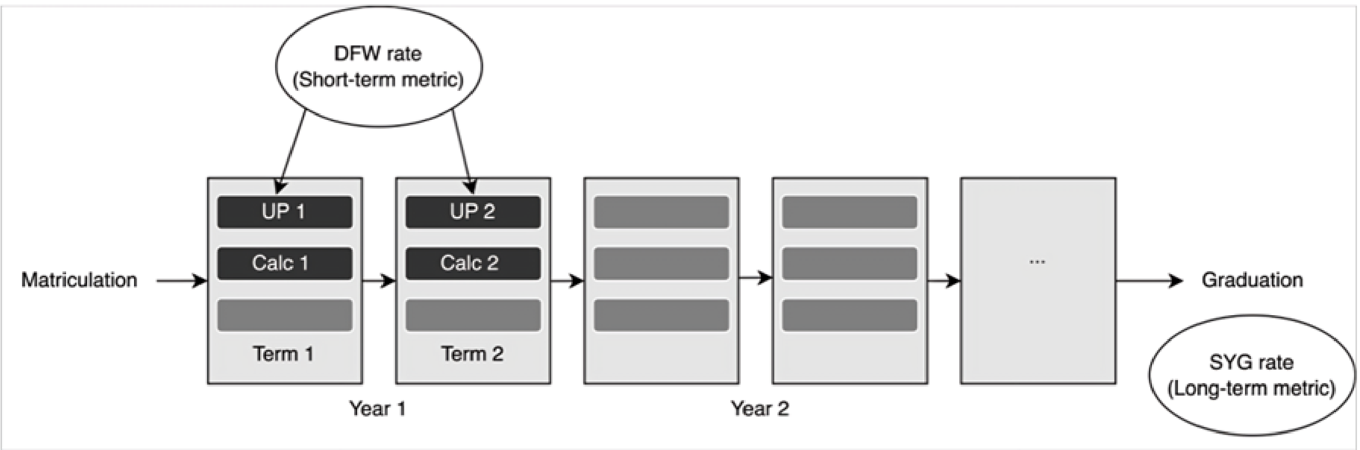


Figure 1. The journey of a STEM student as they transition through college (the dark gray boxes denote courses taken with an LA, allowing us to evaluate the immediate impact of LA exposure using a short-term metric, the DFW rate & over a six-year period, we can assess the effects of LA exposure using a long-term metric, the SYG rate) (Source: Authors)

average (Allen et al., 2015). Previous work has found that undergraduate FG students exhibit a decreased inclination to choose a STEM major and are more prone to switching from initial STEM interest to a non-STEM degree compared to their CG counterparts (Allen et al., 2015). Further studies have found that FG students generally have higher DFW (D, F, or withdraw) rates and lower six-year graduation (SYG) rates (Tedeschi et al., 2023; Van Dusen & Nissen, 2020). Considering the studies emphasizing the necessity for an increase in STEM major graduates, it is essential to identify strategies that enhance success for students from disadvantaged groups.

The use of quantitative analysis methods to study factors related to student academic success in STEM degrees has received significant attention from educational researchers, especially given the continuous advancements in technology (Radunzel et al., 2016; Tedeschi et al., 2023; Van Dusen & Nissen, 2020). One key metric used to gauge student achievement in STEM courses (or programs) is the percentage of students who earn DFW from the course (DFW rate). Many studies have assessed the impact of different educational interventions on student learning outcomes by using the DFW rate as a response variable to quantify these impacts (Ake-Little et al., 2020; Raimondo et al., 1990; Stover & Ziswiler, 2017; Van Dusen & Nissen, 2020). Another common measure of student success is the SYG rate, which tracks the percentage of matriculated students who complete their degree within six years of initial enrollment. Similar to the DFW rate, the SYG rate can serve as a response variable for assessing the impact of different educational interventions on students' academic performance (Boumi & Vela, 2021; Tedeschi et al., 2023). **Figure 1** illustrates a student's academic journey where the DFW rate can be considered as a short-term metric of success and the SYG rate is a long-term metric of success.

There has been extensive research presenting strong evidence of improvement in student performance within STEM courses through the implementation of active learning strategies (Barrasso & Spilios, 2021; Freeman et al., 2014; Von Korff et al., 2016). In these studies, student performance is commonly measured through DFW and SYG rates. One effective academic intervention employed in institutions across the US that promotes the use of active learning pedagogies is the Learning Assistant (LA) model. The LA model isn't a pedagogy itself but rather enables instructors to incorporate active learning pedagogies into their classrooms. The LA model involves students (LAs) aiding their peers through evidence-based collaborative activities in the classroom and during out-of-class help sessions. The LA model includes a pedagogy seminar course that covers a variety of teaching techniques, an assistant position within designated laboratory or lecture classes, and regular meetings with faculty mentors associated with the course (Breland et al., 2023). LAs work closely with faculty mentors to implement teaching activities and strategies that work best for their courses and disciplines. The LA model is currently used in more than 500 institutions worldwide and is incorporated into classes with the goal of enhance courses by aligning them with research-based instructional strategies, benefiting LAs, faculty, and students alike (Learning Assistant Alliance, 2024). LA programs are particularly prevalent in STEM subjects such as biology, chemistry, physics, and mathematics. Numerous studies have shown that LAs are associated with lowering DFW rates and raising SYG rates for marginalized students (e.g., Tedeschi et al., 2023; Van Dusen & Nissen, 2019, 2020).

At the university that is the source of data for this work (referred to in this work anonymously as "UNI"), the LA program hires about 50 undergraduate LAs each semester. At UNI, the LA-supported courses are mostly in mathematics, chemistry, biology, and physics, with the highest use typically in introductory physics and math courses. The first semester that a student works as an LA, they enroll in a 2-credit course on pedagogy that meets once per week. Each LA also meets for an hour per week with their faculty mentor, who is the primary instructor of the course that the LA is supporting. This provides opportunities to review topics and activities for the upcoming week, discuss areas to implement curricular and pedagogical innovations, and devise strategies to clarify concepts that the faculty mentor and/or the LA perceive that students find challenging. LAs also typically hold interactive study sessions outside of class and assist faculty in generating new curricular materials. However, the LA model is intentionally flexible and designed to meet the diverse needs of instructors across a range of disciplines.

Previous work has used regression models to assess the impact that LA support has on students in STEM courses. One common approach is the logistic regression model (or relatedly, a logit regression model), which offers an advantage over ordinary least squares (OLS) regression when analyzing student success metrics (DFW and SYG rates). It is more robust than OLS in handling complex data effectively, without heavy reliance on assumptions. A study by Alzen et al. (2018) found that by using a logistic regression model, exposure to LA support was associated with a 63% reduction in DFW odds for male students and a 55% reduction in DFW odds for female students in gateway STEM courses. Another method for modeling student success in STEM courses is through hierarchical linear models (HLMs) (Van Dusen & Nissen, 2020). HLMs are generalizations of OLS regression and is specifically designed to handle data where observations are clustered within higher-level units (Woltman et al., 2012). These levels could be students within various courses across different college departments. In the case of the student data, using the HLM provides a way to observe the effects of LAs on students within different courses. The HLM approach in this study has been adapted from those used by Van Dusen and Nissen (2020), where they found a strong association between LAs and lower DFW rates in physics courses. These results were especially noticeable for women of color.

One aspect not addressed in any of the existing literature is the assessment on student success for those who have had LA support multiple courses. We are particularly interested in the impact that repeated LA exposure might reveal in STEM courses. Here, we use logistic regression and hierarchical linear regression models to examine these unexplored effects of the LA program by analyzing various combinations of LA exposure within introductory STEM courses as well as how general LA exposure in undergraduate coursework improves student success. By analyzing university ("UNI") student course data, we aim to address the following questions:

1. What impact does the LA program have on students' DFW and SYG rates in introductory STEM courses at UNI
2. How does this impact vary for students belonging to marginalized demographics?
3. How does this impact vary for students with multiple courses that are supported by LAs?

METHODS

Data Description

Our main data set includes 3,574,768 rows where each row corresponds to a course taken by a student at "UNI", distinguished by a unique anonymized student ID number. UNI is a large, private university in the Northeastern US. The course data ranges from 2002 to 2023. Since students are taking many courses throughout their time at UNI, many of the rows correspond to the same student. The main data set includes 33 column features such as *cohort term, degree term, course title, grade, first generation, gender*, and *AALANA*. An additional binary data column was added to account for whether each course taken by the students had LA support. This was done by matching our main longitudinal student grades data set to a LA data set based on whether the course had a match in the *course term, subject, class section,* and *catalog number* data features in both data sets. We added binary columns to account for student demographics (non-male, FG, and AALANA) as well as for DFW and SYG outcomes. The original data set has a gender feature with elements labeled as *M, F,* or *U* (male, female, or undefined). We want majority groups to be our reference group (0s) for the binary features, so we aggregate *F* and the *U* group together as "non-male". We also recognize that male and female are sex not gender, which is an unfortunate limitation of our data. It is important to point out that when students sign up for courses, they have no knowledge of whether the course will include LA support or not. This mitigates potential biases from self-selection. We filtered the data to only include the years 2013–2022 to account for UNI transitioning to a semester system from a quarter system in Fall 2013. All class sections not taken at the US campus of UNI were also eliminated. Summer courses, lab sections, and recitation sections were also filtered from the data set.

We then created two separate data sets, one for DFW analysis and the second for SYG analysis. For the DFW data set, the data were further filtered to eliminate courses offered after Spring 2020 to account for the COVID-19 pandemic. This was done because during the pandemic students had alternative grading options after completing a course, which may bias resulting grades thus affecting the DFW rates. For the SYG data, all students' starting cohort terms were restricted to Fall 2013 to Fall 2016 (inclusive), ensuring we are only incorporating students who have had six full years in the data set. The data were further filtered to only analyze physics 1 and physics 2 (PHYS1 and PHYS2). This was done because PHYS1 and PHYS2 are closely related, so it is reasonable to hypothesize that having an LA in PHYS1 may impact success rates in PHYS2 or having an LA in both PHYS1 and PHYS2 may have an even greater impact.

We were further motivated to analyze this course sequence since they have the highest concentration of LAs among STEM courses at UNI (Tedeschi et al., 2023). A summary of the student demographics for both the DFW and the SYG data can be found in **Table 1**. We anticipate that PHYS1 and PHYS2 may show similar results for student success. To better assess this, multivariable calculus was incorporated into the HLM analysis to evaluate distinct courses. Multivariable calculus has the third-highest LA count at UNI, following PHYS1 and PHYS2. The benefit of using the HLM method is its ability to assess the impact of various data features across multiple levels. This approach provides us with a means of evaluating the impact of the LA program across a broader range of courses. In doing this, two additional data sets were created with the same filtering approaches for DFW and SYG, as the data in **Table 1**. A summary of the demographic statistics for these additional data sets, including multivariable calculus, are presented. **Table 2** shows LA and student counts. We have calculated the previous LA count a student had prior to taking PHYS1 or PHYS2. This is done to analyze the effects previous LA exposure has on a student's DFW odds. This is the same data seen in **Table 1**.

We examine the influence that multiple instances of LA support have on student success by incorporating additional data features. We first added an *LA count* feature to analyze the impact that previous general LA exposure has on a student's academic success. For each student, at any given point during their time at UNI, the value of the *LA count* feature is equal to the number of LA-supported courses that the student has taken prior to the current semester. A student who is currently enrolled in their first LA-supported course would have an *LA count* value of 0, for example. We also added four binary feature groups to account for various combinations of LA support within the physics sequence:

(1) students who have taken PHYS1 with an LA but PHYS2 without an LA,

(2) students who have taken PHYS2 with an LA but PHYS1 without an LA,

(3) students who have taken PHYS1 and PHYS2 with an LA, and

Table 1. Data demographic summaries for students who have taken either PHYS1 or PHYS2 (the DFW data ranges from Fall 2013–Spring 2019 and the SYG data ranges from Fall 2013–Spring 2023)

Gender	Race	FG status	Instruction type	Sample size (DFW)	Sample size (SYG)
Male	AALANA	CG	LA	158	64
			Traditional	293	128
		FG	LA	48	32
			Traditional	106	76
	Non-AALANA	CG	LA	1,836	905
			Traditional	3,534	1,980
		FG	LA	377	216
			Traditional	656	463
Non-male	AALANA	CG	LA	60	29
			Traditional	120	60
		FG	LA	16	9
			Traditional	18	15
	Non-AALANA	CG	LA	502	264
			Traditional	957	566
		FG	LA	104	61
			Traditional	158	113
Total				8,943	4,981

Table 2. LA and student counts-1

LA count	Student count
0	7,811
1	829
2	219
3	63
4	8
5	5
6	5
7	1

Table 3. DFW and SYG

	(PHYS2) LA	(PHYS2) No LA
DFW		
(PHYS1) LA	798	2,314
(PHYS1) No LA	1,467	4,364
SYG		
(PHYS1) LA	370	1,273
(PHYS1) No LA	882	2,456

(4) students who have taken both PHYS1 and PHYS2 without an LA.

We are comparing groups 1–3 to assess what combinations of LA exposure produce the highest success for students in the physics sequence. Identifying these combinations of LA exposure in physics courses was done in order to prep our data to assess the effects of repeated LA exposure in college STEM courses. Summaries of LA exposure among these four student groups can be found in **Table 3**. We see that in our data set, LAs only in PHYS1 has the highest student population among LA integrated courses with only LAs in PHYS2 having the second highest, and LAs in PHYS1 and PHYS2 having the lowest. We present the DFW data set, which is broken down by student demographics, as depicted in **Table 1**, covering 8,943 students. We display the SYG data set, also broken down by student demographic in **Table 1**, encompassing 4,981 students. In both tables, the rows indicate whether the group of students had LA exposure in PHYS1. Similarly, the columns denote whether a student had LA exposure in PHYS2.

Logistic Regression

Logistic regression (or slightly reformulated, logit regression) can be used to analyze both binary outcome variables and outcome variables with multiple categories, making it versatile for a wide range of applications (Cokluk, 2010). Through logistic regression, we can simultaneously examine multiple independent features in relation to the response variable. In the context of our investigation into student success within STEM courses at UNI, logistic regression offers a useful framework for assessing how various factors such as student demographics or LA support in a course, impact the DFW or SYG rate odds. In this study y is the response that we are modeling, and p represents the probability of a given student earning a grade of a D or F or withdrawing from the course (the DFW rate) or alternatively, the probability of a given student graduating within six years of matriculation. In Eq. (1), β_0 signifies the intercept, while $\beta_1, \beta_2, \dots, \beta_n$ denote the coefficients corresponding to the independent features. Within this model, these coefficients align with distinct data features represented by vector $\vec{x} = < x_{LA}, x_{NonMale}, x_{FG}, x_{AALANA} >$. Through some algebraic manipulation (Eq. [2]), the coefficients in the logistic regression model can be interpreted as quantifying the influence that each independent data feature has on DFW and SYG rate odds.

$$y = p(\vec{x}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{LA} + \beta_2 x_{NonMale} + \beta_3 x_{FG} + \beta_4 x_{AALANA})}} \quad (1)$$

$$p = \frac{e^{\beta_0 + \beta_1 x_{LA} + \beta_2 x_{NonMale} + \beta_3 x_{FG} + \beta_4 x_{AALANA}}}{e^{\beta_0 + \beta_1 x_{LA} + \beta_2 x_{NonMale} + \beta_3 x_{FG} + \beta_4 x_{AALANA}} + 1}$$

$$ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_{LA} + \beta_2 x_{NonMale} + \beta_3 x_{FG} + \beta_4 x_{AALANA}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 x_{LA} + \beta_2 x_{NonMale} + \beta_3 x_{FG} + \beta_4 x_{AALANA}}$$

$$\frac{p}{1-p} = e^{\beta_0} e^{\beta_1 x_{LA}} e^{\beta_2 x_{NonMale}} e^{\beta_3 x_{FG}} e^{\beta_4 x_{AALANA}}. \quad (2)$$

Since p can be interpreted as the DFW or the SYG rate, $p/(1-p)$ represents the odds of a student receiving a D, F, or W grade, or graduating within six years of matriculation. The features $x_{LA}, x_{NonMale}, x_{FG}, x_{AALANA}$, are binary (0 or 1), so each of the factors

Table 4. Data demographic summary for students who have taken either PHYS1 and PHYS2, or multivariable calculus (the DFW data ranges from Fall 2013–Spring 2019 and the SYG data ranges from Fall 2013–Spring 2023)

Gender	Race	FG status	Instruction type	Sample size (DFW)	Sample size (SYG)
Male	AALANA	CG	LA	257	123
			Traditional	358	137
		FG	LA	103	74
			Traditional	121	79
	Non-AALANA	CG	LA	2,464	1,242
			Traditional	3,915	1,994
		FG	LA	569	355
			Traditional	715	465
Non-male	AALANA	CG	LA	93	49
			Traditional	134	63
		FG	LA	26	18
			Traditional	24	16
	Non-AALANA	CG	LA	586	316
			Traditional	1,001	564
		FG	LA	143	84
			Traditional	166	112
Total				8,943	4,981

$e^{\beta_1}, e^{\beta_2}, e^{\beta_3}, e^{\beta_4}$ represents the multiplicative influence on the odds ratio for DFW or SYG rates. If these factors are less than one, then presence of the associated features (e.g., x_{FG}, representing an FG college student) will diminish the odds of a DFW or SYG. On the other hand, if these factors are greater than one, the presence of such associated features will increase the odds of a DFW or SYG. In this way, these exponentiated coefficients provide insights into the factors affecting student success in college STEM education.

We estimate the coefficients $\beta_1, \beta_2, \ldots, \beta_n$ in the logistic regression model using maximum likelihood estimation (MLE), employing the Newton-Raphson algorithm. MLE operates by identifying the coefficient values that maximize the likelihood function, quantifying how effectively the model describes the observed data. We fit the logistic regression model using the statsmodels Python package (Perktold et al., 2024).

To quantify the uncertainty of how each feature affects the probability of the DFW or SYG rate, the standard error (SE) for each coefficient was calculated using the square root of the variance $SE_i = \pm\sqrt{Var(\beta_i)}$. We calculated the error bounds by exponentiating the SEs and then using these to compute upper and lower bounds for each coefficient. It's important to note that since odds are calculated by multiplying e^{β_i} values, they cannot be negative. While the logistic regression model provides us with valuable insight into the impact of LA participation on student success, it does not capture the grouped multi-level structure inherent to student data. To examine student in separate STEM courses more comprehensively, a more suitable modeling approach may be an HLM particularly adept for the inherently hierarchical structure of student grade data (Van Dusen & Nissen, 2020).

Hierarchical Linear Modeling

Students' grades are inherently hierarchical, as they involve students nested within courses, and courses nested within departments. Consequently, the HLM approach is an effective method for examining the impact of the LA program on student success across various demographics and courses. To enhance the depth of our model, we incorporated multivariable calculus into the data set alongside PHYS1 and PHYS2 (as shown in **Table 4**). By including multivariable calculus in the HLM, we can assess the variation in the LA program's impact beyond physics courses. Before expanding on the HLM, we will first define the classical OLS regression equation:

Table 5. LA and student counts-2

LA count	Student count
0	9025
1	1166
2	340
3	109
4	22
5	8
6	4
7	1

$$y = p(\vec{x}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon \quad (3)$$

In the OLS equation, y is the response variable, p is a probability, β_0 is the intercept, $\beta_1 \ldots \beta_n$ are the coefficients, $x_1 \ldots x_n$ are the data features, and ϵ is the random noise associated with the estimates. The HLM approach builds upon this concept, expanding OLS to account for different groups. We can visualize the HLM as a matrix, where each row represents an individual OLS equation:

$$y_i = p_i(X) = \alpha_i + \beta_{ij} X_{ij} + \epsilon_i \quad (4)$$

In the HLM framework, the i subscript denotes the matrix row (or the individual OLS equation) and the j subscript denotes the matrix column. In Eq. (4), y is the i^{th} response that we are modeling corresponding to the probability p_i. The intercept is captured in α_i associated with the specific course under observation, and X is an $n \times m$ matrix. The coefficients β_{ij} represents the effects of LA exposure and the student demographics corresponding to the different STEM courses while ϵ_i is the random noise associated with the estimates. Similar to the logistic regression model, we constructed the HLM using the Python package statsmodels and the coefficients were calculated using the same MLE method. A summary of the student demographics is provided in **Table 4** following the incorporation of multivariable calculus into the analysis. These findings are discussed further in the results section. **Table 5** shows LA and student counts.

Table 6. DFW and SYG rates comparison for students who have taken either PHYS1, PHYS2, or both with and without LA support

Group (PHYS 1 and PHYS2)	DFW rate	SYG rate
Students with LA	0.19	0.85
Students without LA	0.26	0.84

Table 7. Comparison of DFW and SYG rates across four groups: (1) AALANA students with LA support, (2) AALANA students without LA support, (3) non-AALANA students with LA support, and (4) non-AALANA students without LA support

Group (PHYS 1 and PHYS2)	DFW rate	SYG rate
AALANA with LA	0.29	0.81
AALANA without LA	0.39	0.82
Non-AALANA with LA	0.18	0.85
Non-AALANA without LA	0.24	0.85

Similar to **Table 2**, we have calculated the previous LA count a student had prior to taking PHYS1, PHYS2, or multivariable calculus. This is done to analyze the effects previous LA exposure has on student DFW rates. This is the same data seen in **Table 4**.

RESULTS

Prior to fitting the logistic regression or HLMs, we conducted preliminary calculations as a reference to verify the models' results. These calculations were made to analyze students enrolled in courses with LA integration who received grades of DWF from the course and compared this against the overall student population in PHYS1 and PHYS2, regardless of their grade. We conducted a similar analysis for students without LA integration in their courses. We repeated this process for SYG rates as well. The results of these calculations are presented in **Table 6**. Based on these preliminary calculations, we found a 7% reduction in DFW rates for the two introductory physics courses with LA integration compared to those without. Conversely, we found there was only a marginal 1% increase in SYG rates for students with LA incorporation in their courses compared to those without.

We also made similar comparisons for AALANA student seen in **Table 7**. Based on these results (**Table 7**), there is a 10% reduction in DFW rates for AALANA students with LA support in PHYS1 and PHYS2 whereas non-AALANA students have a 6% reduction in DFW rates (**Table 7**). There is a 1% reduction in SYG rates for AALANA students with LA integration and non-AALANA students saw no change in LA integration.

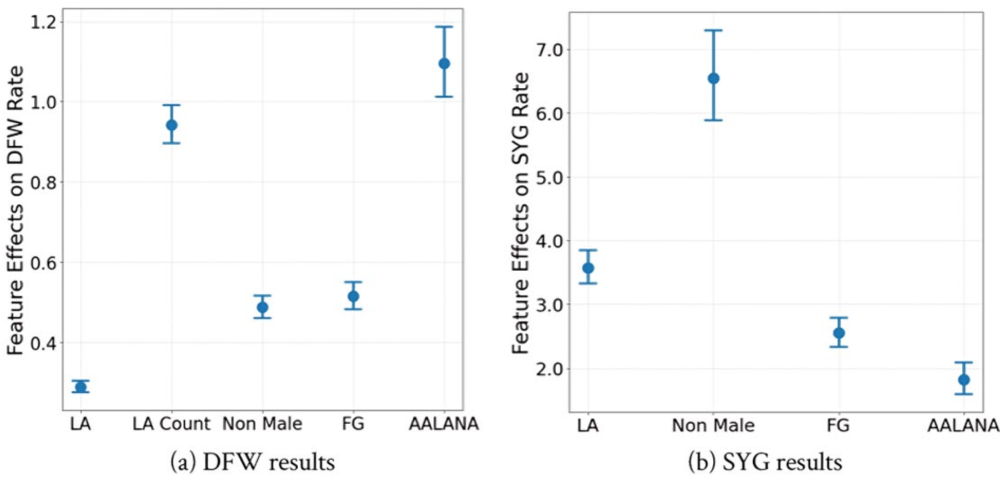
The results in **Table 6** and **Table 7** show LA support is associated with substantial benefits in terms of decreased DFW rates, but no significant change in graduation rates when studying PHYS1 and PHYS2 specifically. These calculations indicate that LA integration has a more modest impact on students' graduation rates in PHYS1 and PHYS2, than on DFW rates.

Logistic Regression

In our first assessment of the student data using the logistic regression model, we incorporated all the data features, LA, non-male, and AALANA students, as well as the LA count feature to the DFW analysis. The results are illustrated in **Figure 2**, where we examine the exponentiated coefficients in relation to the DFW and SYG rates. The influence of current LA support on the odds of a student earning a D, F, or withdrawal from a course are approximately 0.3 (part a in **Figure 2**), indicating a notable impact on reducing the DFW rate. We also find that previous general LA support is less impactful on lowering student DFW odds as seen by the LA count exponentiated coefficients which is approximately 0.95. Additionally, the non-male and FG data features are associated with a statistically significant reduction in the DFW rate. However, for AALANA student demographic data feature, the exponentiated coefficient error bounds overlap 1 in part a in **Figure 2**, and so we can't conclude that there is a significant relationship between AALANA status and changes in DFW rate. In part b in **Figure 2**, we analyze the odds of students' SYG rates. Here, odds greater than one show a positive effect on the SYG rate, while values between 0 and 1 suggest a reduction in the odds of students graduating within six years. In part b in **Figure 2**, the AALANA student data feature is relatively close to zero, indicating a small impact on SYG or DFW rates.

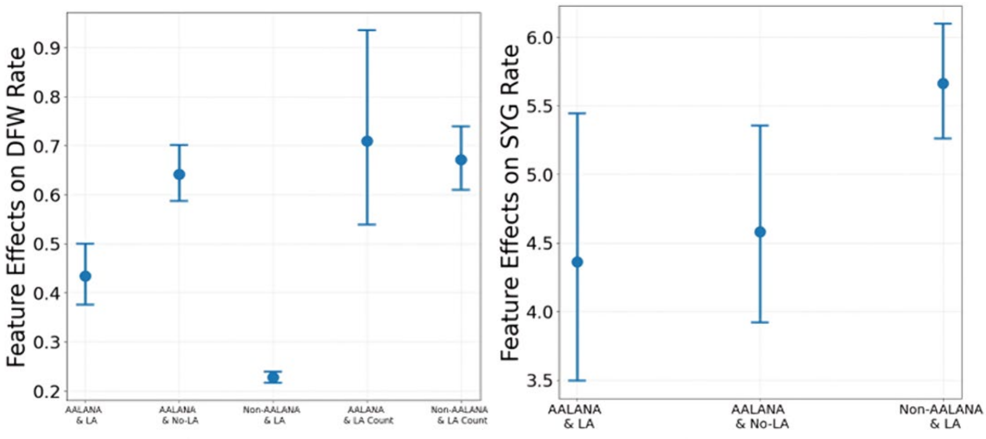
Given that LAs have, in general, been found to be beneficial to students across demographic groups, yet we did not observe substantial effects on DFW odds for AALANA students in PHYS1 and PHYS2 (part a in **Figure 2**), we subdivided the PHYS1 and PHYS2 students into four groups based on LA exposure and AALANA status:

(1) AALANA students with LA support,



(a) DFW results (b) SYG results

Figure 2. Logistic regression results with LA, non-male, FG status, and AALANA students as the independent features (the LA count feature was also incorporated into the DFW analysis: [a] displays the feature odds of students' DFW rates and [b] displays the feature odds of students' SYG rates) (Source: Authors)



(a) DFW results (b) SYG results

Figure 3. Logistic regression results where the features are AALANA students with an LA in at least PHYS1 or PHYS2, AALANA students without an LA in both PHYS1 and PHYS2, non-AALANA students with an LA in at least PHYS1 or PHYS2, and non-AALANA students without an LA in both PHYS1 and PHYS2: (a) displays the feature odds of students' DFW rates with additional LA count groups and (b) displays the feature odds of students' SYG rates (Source: Authors)

(2) AALANA students without LA support,

(3) non-AALANA students with LA support, and

(4) non-AALANA students without LA support.

For the logistic regression analysis on DFW odds, we incorporated two additional AALANA status groups: AALANA students with LA counts and non-AALANA students with LA counts. Eq. (5) displays the DFW logistic regression analysis on the AALANA groups. We are interested in interactions between AALANA status and LAs, to characterize how the effects of LA support may be felt differently for AALANA and non-AALANA students. We are also interested in how the effects of general previous LA support differs from that of LA support in a current course for AALANA students. We broke the students up so that each one belongs to exactly one of these subgroups based on their AALANA status and whether they had LAs in PHYS1 and/or PHYS2 (**Table 7**). Additionally, we considered whether a student had LA support in any previous course based on the LA count. We represent membership in these groups as binary features in the logistic regression analysis, taking non-AALANA students with no LA support as the reference group.

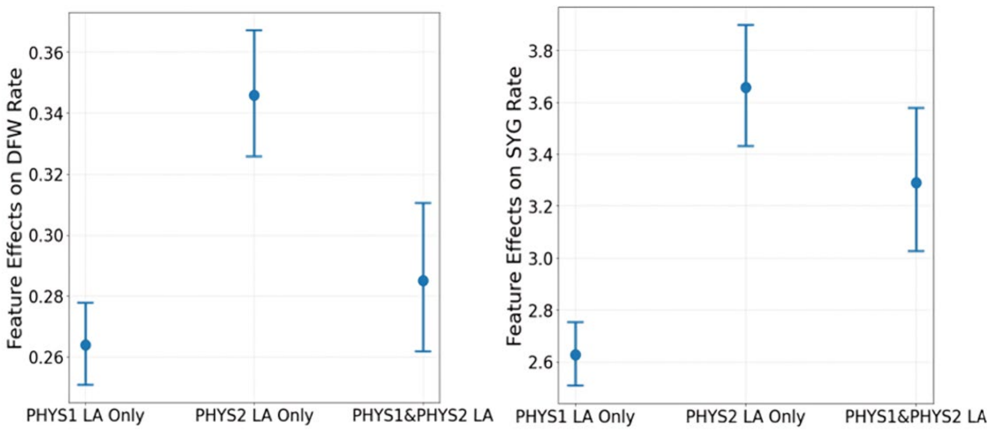
$$ln\left(\frac{p_{DWF}}{1-p_{DFW}}\right) = \beta_0 + \beta_1 x_{AALANA\,\&\,LA} + \beta_2 x_{AALANA\,\&\,no-LA} + \beta_3 x_{non-AALANA} + \beta_4 x_{AALANA\,\&\,LA-Count} + \beta_5 x_{non-AALANA\,\&\,LA-Count} \quad (5)$$

We find that non-AALANA students who had LA exposure in PHYS1 and PHYS2 exhibit the most impact on lower odds of earning a DWF from a course (part a in **Figure 3**). However, we still find a notable impact on reducing the odds of the DFW rate for AALANA students who had LA exposure in PHYS1 and PHYS2 compared to those who did not. Additionally, the resulting feature coefficients for the LA count groups indicate that AALANA students benefit more than non-AALANA students from having previous LA exposure, based on the lower DFW odds (part a in **Figure 3**). Even after accounting for AALANA student demographics, we do not find a significant impact of LA exposure on AALANA students SYG odds, irrespective of LA integration (as depicted in part b in **Figure 3** from the overlapping error bars). The logistic regression results for both DFW and SYG rates based on AALANA integration agree with the results depicted in **Table 7**.

Using the logistic regression model, we now assess the level of LA exposure based on the groupings displayed in **Table 3**, which are categorized by LA exposure for students with an LA in only PHYS1, only PHYS2, or both PHYS1 and PHYS2. We found that LA exposure in only PHYS1 produces DFW odds of 0.26, LA exposure in only PHYS2 results in DFW odds of 0.34 and having LA support in both PHYS1 and PHYS2 results in DFW odds of 0.28. In all three cases, having LA support in one of these combinations lowers the DFW odds relative to students without LA support in either course (part a in **Figure 4**). We also find that students having an LA in PHYS1 or having an LA in both PHYS1 and PHYS2 lowers the DFW odds more than just having an LA in PHYS2. In part b in **Figure 4**, the error bounds for the influences of LAs in PHYS2 only and LAs in both PHYS1 and PHYS2 (right two columns of part b in **Figure 4**) are overlapping. This indicates that we cannot conclude that there is a meaningful difference between the two groups. But the error bounds for the feature of having LA integration in both PHYS1 and PHYS2 (part b in **Figure 4**, right column) do not overlap with the error bounds for the feature of having an LA PHYS1 only (part b in **Figure 4**, left column). While these are not strictly confidence intervals, the relative magnitudes and uncertainties suggest that there is a benefit to having an LA in PHYS1 and PHYS2 versus just in PHYS1 in relation to students' SYG rates.

Hierarchical Linear Modeling

To deepen our analysis using the HLM, we included multivariable calculus. This additional class was incorporated to examine how student success varies across STEM courses. In the HLM analysis, we present the coefficient values, denoted as β_i, as either positive or negative, where positive coefficients raise the HLM output and negative coefficients decrease the HLM output. Here, the outputs are the metrics of success, which are either the DFW rate or SYG rate. **Figure 5** illustrates the effects of various data features on the DFW rate. We find that LA exposure in multivariable calculus appears to have a stronger effect on lowering the DFW rate with a coefficient value of approximately –0.12 compared to LA exposure in either PHYS1 or PHYS2 which are approximately –0.35 and –0.5. Furthermore, being



(a) DFW results (b) SYG results

Figure 4. Logistic regression results where the features are students with an LA in PHYS1 only, PHYS2 only, or an LA in both PHYS1 and PHYS2: (a) displays the feature odds of students' DFW rates and (b) displays the feature odds of students' SYG rates (Source: Authors)

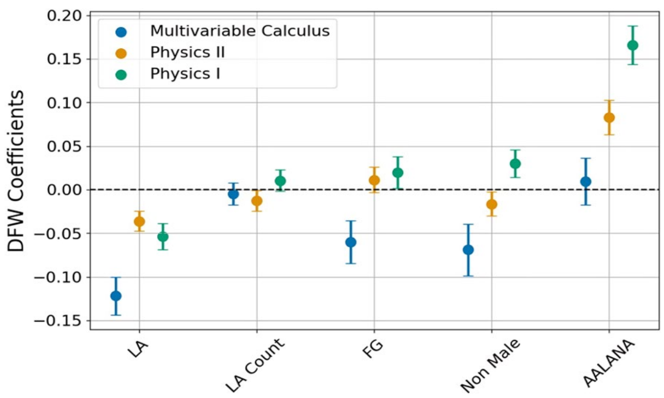


Figure 5. HLM results with the DFW rate as the response variable and LA, FG, non-male, and AALANA students as the independent data features (the coefficients are grouped by the courses multivariable calculus, PHYS1 and PHYS2) (Source: Authors)

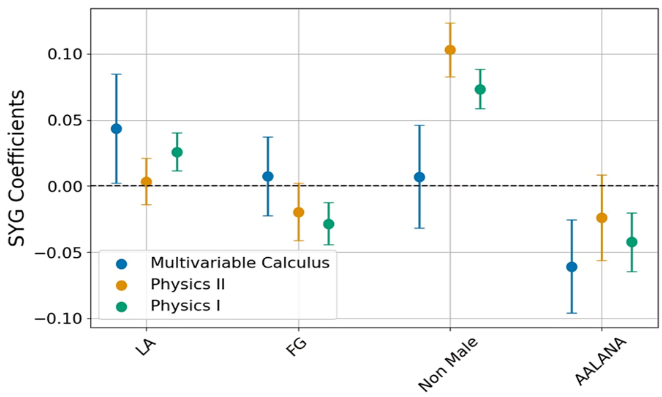


Figure 6. HLM results with the SYG rate as the response variable and LA, FG, non-male, and AALANA students as the independent data features (the coefficients are grouped by the courses multivariable calculus, PHYS1 and PHYS2) (Source: Authors)

either an FG student or a non-male student reduces the DFW rates in multivariable calculus. However, for PHYS1 and PHYS2, the FG coefficient error bounds overlap with zero (**Figure 5**), and the non-male coefficient error bounds are near zero, indicating that these students are not significantly affected based on their marginalized demographics.

Additionally, for PHYS1 and PHYS2, AALANA students have a higher probability of receiving a DWF from a course, as indicated by slightly positive coefficients. These effects on AALANA students align with the results from Van Dusen and Nissen (2020). However, as observed from the preliminary calculations in **Table 7**, AALANA students with LA support showed a 10% decrease in their DFW rates. Therefore, this suggests that whatever disadvantage AALANA students face in these courses, LA support is a viable avenue to reduce those numbers.

Using the same three STEM courses and data features, we applied the HLM with the SYG rate as the response variable (**Figure 6**). We find that for the SYG rate across all three STEM courses, the LA coefficients are all greater than zero, indicating a positive effect on students graduating within six years. These findings corroborate with the preliminary calculations shown in **Table 3**, where we observed only a 1% difference in graduation rates among students in PHYS1 and PHYS2 with or without LA exposure. Similarly, we observe a consistent trend for non-male students, as seen in the logistic regression results, showing a higher probability of graduating within six years in PHYS1 and PHYS2. However, for multivariable calculus, the error bounds for the non-male coefficient include 0 so it isn't statistically significant. This may be attributed to relatively smaller sample sizes for non-male students in multivariable calculus.

DISCUSSION

Research Question 1

What impact does the LA program have on students' DFW and SYG rates in introductory STEM courses at UNI? We found, using the logistic regression model, that LA support in PHYS1 or PHYS2 is associated with a decrease in DFW odds, which is consistent with previous studies (Alzen et al., 2018). The HLM results showed that having an LA in either PHYS1 or PHYS2 yields similar impacts on DFW rates, with the HLM displaying that the LA coefficients for PHYS1 and PHYS2 differ by only 2% (**Figure 5**). Additionally, the HLM revealed that the impact of LA support in multivariable calculus was much stronger than in either of the physics courses. Furthermore, the logistic regression model indicated that LA support in PHYS1 or PHYS2 is associated with an increase in graduation rates. Using the HLM model, we observed the positive impact that LAs have in each course individually. Our findings that LA support in these introductory science courses is associated with improvements in graduation rates are consistent with previous work (Tedeschi et al., 2023). However, the effect of LA support on SYG rates is relatively lower than the improvement of +9% found by those authors. One explanation for the less pronounced SYG impact may be that PHYS1 and PHYS2 already have some form of course support (e.g., teaching assistants, recitations), which might diminish the expected effect. It may also be the case that the effects of the LA program on SYG rates were less pronounced for PHYS1 and PHYS2 due to the graduation rates already averaging around 85%, much higher than the UNI average. Further, the fact that these introductory Physics courses generally are taken early during a student's time at UNI means that many other events will also occur after students take PHYS1 or PHYS2, before graduating (or not). Thus, many other events can confound any causal relationship between LA support in PHYS1 and PHYS2 and students' likelihood of graduating.

Research Question 2

How does the impact of LA support vary for students belonging to marginalized demographics? In our analysis of the logistic regression results, we found that after controlling LA exposure among AALANA students, their DFW odds were reduced by 20%. When comparing previous general LA support among AALANA students to AALANA students who didn't have previous LA support, the effects on DFW odds were nearly the same. When using logistic regression to analyze LA support's impact on SYG rates among AALANA students, we saw no difference in SYG rates between AALANA students in LA-supported versus non-LA-supported introductory physics courses. This, too, may be attributable to the typical long time periods between when students would take an introductory physics course (i.e., early in their college career) and graduating.

Research Question 3

How does the impact of LA support vary for students with multiple courses that are supported by LAs? Our logistic regression model results indicate that repeated LA exposure in physics courses significantly benefits DFW rates beyond just having an LA in PHYS2. An LA in PHYS2 alone shows improvements compared to no LA support, but having an LA in both PHYS1 and PHYS2, or even just in PHYS1, reduces DFW odds more than having an LA solely in PHYS2. This finding was unexpected. One possible explanation is that students who had LA support earlier, in PHYS1, developed better problem-solving skills, which had a positive impact on their performance in subsequent courses. This is an area we plan to investigate further. Additionally, our analysis suggests a significant benefit in SYG rates when students receive LA support in both PHYS1 and PHYS2 compared to just PHYS1. It is essential to lower DFW rates while simultaneously increasing SYG rates. As illustrated in **Figure 4**, incorporating LA support into both PHYS1 and PHYS2 appears to yield the best outcomes for both success metrics. Therefore, we conclude that providing LA support in both PHYS1 and PHYS2 could be an effective strategy for enhancing STEM student success in introductory physics courses at UNI. These results offer practical guidance on the potential positive impacts of LA support, including repeated support in multiple courses, more broadly as well.

CONCLUSION

This study underscores the impactful role of the LA program in enhancing student success, particularly through significant reductions in DFW rates observed across multiple introductory STEM courses. Logistic regression and HLM analyses consistently revealed the positive impact of LA integration, with notable improvements in both introductory physics and multivariable calculus courses. The impact of LA support for AALANA students in the observed introductory STEM courses resulted in a substantial reduction in DFW odds (20%), highlighting the program's effectiveness in supporting marginalized demographics. Repeated LA exposure yielded cumulative benefits, suggesting that early and sustained LA support fosters essential problem-solving skills that contribute to long-term success. However, the impact on SYG rates, while positive, was less pronounced. This is likely due to preexisting support structures, already relatively high baseline graduation rates, and the simple fact that there is a lot of time between student enrollment in these introductory STEM courses (students' first or second year at UNI) and on-time graduation (four or five years in most UNI programs).

Future work should focus on the longitudinal impacts of LA exposure, specifically its role in sustaining student success across advanced STEM courses. Investigating the complex factors influencing SYG rates, particularly for AALANA students, will be essential to addressing existing disparities and improving equity. Additionally, further studies should evaluate how varying combinations and durations of LA support optimize outcomes, offering insights to refine program implementation. These findings advocate for enhancing the LA program by emphasizing early intervention and repeated engagement, thereby driving academic achievement and inclusivity across diverse student populations.

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