

EQUITABLE STATISTICS EDUCATION THROUGH ACTIVE LEARNING

by

ALIANN XU

(Under the Direction of Abhyuday Mandal)

ABSTRACT

This thesis, conducted as part of the Active Learning Change Grant, examines the effectiveness of active learning techniques incorporated in large lecture-format classrooms, with a focus on STAT 2000. In Spring 2024, a survey was administered to all enrolled students to collect data on their classroom experiences and demographic profiles. The study examined whether the test performance of LGBTQIA students varied depending on whether they were in active learning or traditional classroom settings. Specifically, we analyzed students' cumulative test scores using multiple linear regression, multinomial regression, and linear mixed models. Based on one semester of data, the analysis revealed no statistically significant differences in test outcomes for LGBTQIA students between the two classroom types. Although the result did not indicate a significant difference, these findings contribute to our ongoing efforts to refine inclusive teaching practices and to understand how active learning impacts diverse student populations.

INDEX WORDS: Introductory Statistics, Statistics Education, Active Learning, LGBTQIA
Students

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ALIANN XU

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ALIANN XU

Major Professor: Abhyuday Mandal

Committee: Ray (Shuyang) Bai
Mudiyanselage Dassanayake

Electronic Version Approved:

Ron Walcott

Dean of the Graduate School

The University of Georgia

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CHAPTER I

INTRODUCTION

Diversity in STEM fields can lead to innovations and breakthroughs, yet the underrepresentation and mistreatment of marginalized populations in STEM fields can hinder this unique edge of the field (Cech and Waidzunus, 2021; Hughes, 2018). One such group is the LGBTQIA community, which includes individuals identifying as lesbian, gay, bisexual, transgender, queer, intersex, and/or asexual. During the past decade, the percentage of the U.S. population identifying as LGBTQIA has doubled, accompanied by greater societal acceptance (Jackson et al., 2024; Payne and Smith, 2011). Despite this progress, ample evidence shows LGBTQIA individuals deal with bias and exclusion in academic environments (Cech and Waidzunus, 2021; Gates, 2015; Henning et al., 2019; Hughes, 2018; Voigt, 2022).

As a result, due to their small percentage in the population and the reluctance of some to come out, these students often become an "invisible minority" (Lopez & Chims, 1993, p. 97). As a result, STEM classrooms can be particularly challenging for LGBTQIA students (Cooper and Brownell, 2016), especially in active learning environments. Active learning, broadly defined as "any instructional method that engages students in the learning process" (Prince, 2004, p. 223).

Unlike traditional lectures, where students can passively listen to lectures, active learning forces them to engage directly with peers and instructors. These interactions may exacerbate existing discomfort. The unique challenges faced by LGBTQIA students in active learning environments motivated my research. In particular, for this study, we examined the relationship between the LGBTQIA students' attitudes

toward active learning and exam performances in Introductory Statistics (STAT 2000) at the University of Georgia.

1.1 Literature Review

Despite the growing research on LGBTQIA individuals' experiences in STEM work and school environments, their unique challenges in active learning settings remain underexplored. Existing evidence suggests that these individuals often face discrimination, microaggressions, and a lack of inclusivity. Indeed, a study conducted by Cooper and Brownell (2016) revealed that LGBTQIA students often perceive active learning environments as unwelcoming and exclusionary. When assigned to new groups, they frequently gauged their peers' acceptance, frequently encountering microaggressions and transphobic interactions with peers and instructors instead. One participant remarked,

I feel like a lot of the times I've heard homophobia from students hidden behind the fact that they're not trying to seem homophobic. I think that's the new thing now—it's not acceptable to be homophobic—but people still are, so they do show their prejudice in different ways (Cooper & Brownell, 2016, p. 7).

Similarly, Henning et al. (2019) found that queer, bisexual, and pansexual students expressed less favorability toward active-learning pedagogies (ALPs), such as small group discussions, and perceived them as less inclusive compared to their homosexual and heterosexual peers.

This emotional burden, coupled with ambivalence about whether to disclose their sexual identity, increases their cognitive load. These challenges detract from their ability to focus on academic content (Cooper and Brownell, 2016; Lopez and Chims, 1993). Moreover, studies show that LGBTQIA individuals experience higher levels of Fear of Negative Evaluation (FNE), a specific anxiety linked to unfavorable social judgment, in active-learning science courses (Busch et al., 2023; Jackson et al., 2024). In response, students tend to overthink their responses and are less willing to participate. Another student stated, "There's no way you can go through fifteen (course) hours when you're going through this." (Lopez & Chims, 1993,

p. 98). Others feared that disclosing their identity might result in being graded unfairly, patronized, or becoming the target of unwanted attention. In alignment with what's just discussed, Voigt (2022) showed that LGBTQIA students reported lower math engagement, lower participation and interaction levels compared to other groups. Similarly, Lopez and Chims (1993) found that students at Ohio State University hesitated to come out due to societal norms, internalized stigma, fear of rejection and experiencing a sense of isolation.

Despite the aforementioned challenges, active learning environments facilitate empowering relationships between students, especially those in underrepresented and discriminated communities, and the merits of active learning sometimes counteract its potential drawbacks. For instance, literature seems to agree a supportive environment can help counteract the aforementioned challenges by fostering relationships, reducing academic stress, and emphasizing retention (Cooper and Brownell, 2016; Kroll and Plath, 2021; Voigt, 2022). The increased interaction between students and instructors allows students form supportive relationships with peers who share similar identities. As one student noted, "I wouldn't have met two other LGBTQIA people if I wouldn't have introduced myself the way that I did, and then they wouldn't have someone they could relate to also" (Cooper & Brownell, 2016, p. 11).

This thesis contributes to the literature on LGBTQIA students' experiences in active learning classrooms. Firstly, previous literature is largely focused on qualitative aspects—for example, how negative interactions with peers and instructors can hinder students' experiences, and how connecting with others who share similar identities can foster encouragement and support. While we acknowledge LGBTQIA student's experiences in these classrooms, our study shifts the focus to examining how the learning environment impacts academic performance from a quantitative perspective. Secondly, most existing research has primarily examined students' experiences in math and life science courses. Our study extends this research by focusing on these dynamics in statistics classrooms. Specifically, we aim to evaluate whether active learning improves the total test performance of students based on their LGBTQIA status, including both those who openly identify and those who chose not to disclose.

To extend the current research on LGBTQIA students' experiences in active learning classrooms, this thesis contains three additional chapters. Chapter 2 describes the dataset and presents exploratory data analysis to identify key patterns and relationships. It also outlines the statistical methods and models used in the study. Chapter 3 presents the results of the analysis. Finally, chapter 4 summarizes our findings, discusses limitations, and suggests potential avenues for future research.

CHAPTER 2

DATA AND MODEL SELECTION

2.1 Data Description

Each fall and spring semester, over 1,000 students take STAT 2000. The students are divided into multiple large lecture sections, each with approximately 150 students. Aside from attending these lecture hall classes, students enroll in smaller lab sections, each identified by a unique Course Reference Number (CRN). In Spring 2024, six lecture sections were offered, taught by four different instructors. Of these, five incorporated active learning techniques, while one followed a traditional lecture format. Accordingly, of the 36 lab sections (CRNs), 30 were linked to active learning lectures and six to the traditional lecture. Despite variations in instruction, all sections followed the same curriculum and administered identical exams, ensuring consistency and allowing for meaningful comparisons of students' performance, important for our research. The course included four exams and quizzes throughout the semester, none of which were cumulative.

As part of an Active Learning Change Grant awarded to Dr. Dassanayake, Dr. Mandal, and Mr. Nicholas Toeppen, a study was developed to assess the impact of active learning strategies in STAT 2000. In collaboration with the grant team, a student survey was created to gather information on academic background, demographics, learning preferences, and classroom experiences. Dr. Dassanayake also led the process of obtaining University of Georgia Institutional Review Board approval for the study

(PROJECT00008308). A Qualtrics survey and cover letter were then prepared and shared with Mr. Toeppen, the STAT 2000 course coordinator, who distributed them to students during the semester. Participation was voluntary, and responses were anonymized and linked to academic performance data to enable further analysis.

To help answer our research questions, we received an Excel spreadsheet with the student survey responses collected in Spring 2024. The complete raw dataset consists of 657 students' observations, each with the 39 survey questions and students' grades on the four quizzes and four exams. The first variable of interest is **LGBTQIAStatus**, which represents students' self-identification with the LGBTQIA community. Another key variable is **ActiveLearningSection**, which represents which section of STAT 2000 the students are enrolled in. As previously mentioned, 30 of the 36 sections incorporated active learning techniques. In particular, using the CRN identifiers provided in the course data, we classified sections known to have used active learning as "yes" and all the others as "no." Other key demographic variables include **ResidenceType**, **HouseholdIncome**, **DRCRegistration**, **Race**, and **Sex**. We are also interested in how students scores on each exam, which are represented by **Test1Grade**, **Test2Grade**, **Test3Grade**, and **Test4Grade**, respectively. A full description of every variable in the data set can be found in the data dictionary in Appendix A.

Our analysis focuses on the 618 students who explicitly provided consent to participate. In other words, students who completed the survey but did not consent to having their responses included in the analysis were omitted. Moreover, the data set has approximately 10.8% missing data, and all data cleaning and analyses were conducted using R Statistical Software (R Core Team, 2023a). Since there was a small percentage of missing values, we dropped all the missing values, using the **na.omit()** function from the R package **Tidyverse** (Wickham et al., 2019). Moreover, to simplify calculations, we summed the students' four exams grades, using the **rowSums()** function in Base R (R Core Team, 2023a). Thus, students' test grades were out of 400 points. We denoted this new variable as **TotalTestGrade**. As part of the cleaning process, we excluded one student who only completed a single exam and received a **TotalTestGrade** of

5 out of 400 points. This extremely low score, relative to the rest of the dataset, could have skewed the results.

Since none of the exams or quizzes were cumulative, it was necessary to consider students' overall performance across *all* exams rather than focusing on any single test or quiz. That said, for the purpose of this thesis, we will only focus on students' test grades.

2.2 Exploratory Data Analysis

To begin our data exploration, we focused on the responses to the question "Do you identify as a member of the LGBTQIA community?" Of the 618 students, 64 identified as LGBTQIA and 24 chose not to disclose their status. Given our research focus, these two groups are our subjects of interest. Indeed, our research is interested in examining the perceived effectiveness of active learning techniques on openly LGBTQIA individuals, versus those who identify as queer but have not come out yet. We anticipate that those whose sexual preferences remains private will view active learning as less helpful than those who are openly LGBTQIA.

Next, we analyzed LGBTQIA students' experiences in active learning classrooms by exploring the patterns between LGBTQIA identity and key active learning experience responses. Table 2.1 shows the breakdown of the enrollment of students in active learning and traditional classrooms based on LGBTQIA status. Notably, approximately 70% of definite or possible LGBTQIA students were enrolled in active learning classrooms.

Table 2.1: Counts of students enrolled in active learning and traditional classroom courses by LGBTQIA status.

LGBTQIA Status	Active Learning	Traditional Classroom	Total
Prefer not to say	15	9	24
Yes	46	17	63
Total	61	26	87

2.2.1 Students' Perceptions of Active Learning Environments

We then created these bar charts with the **ggplot()** function from the **ggplot2** package (Wickham, 2016). In particular, we started by examining whether students believed that active learning techniques enhanced their understanding of course material compared to traditional lectures. According to Figure 2.1, openly LGBTQIA students reported higher levels of agreement, with 49.2% somewhat agreeing and 19.0% strongly agreeing that active learning helped them understand concepts better. In contrast, among students who preferred not to disclose their LGBTQIA status, 37.5% neither agreed nor disagreed, and only 12.5% strongly agreed with the effectiveness of active learning techniques.

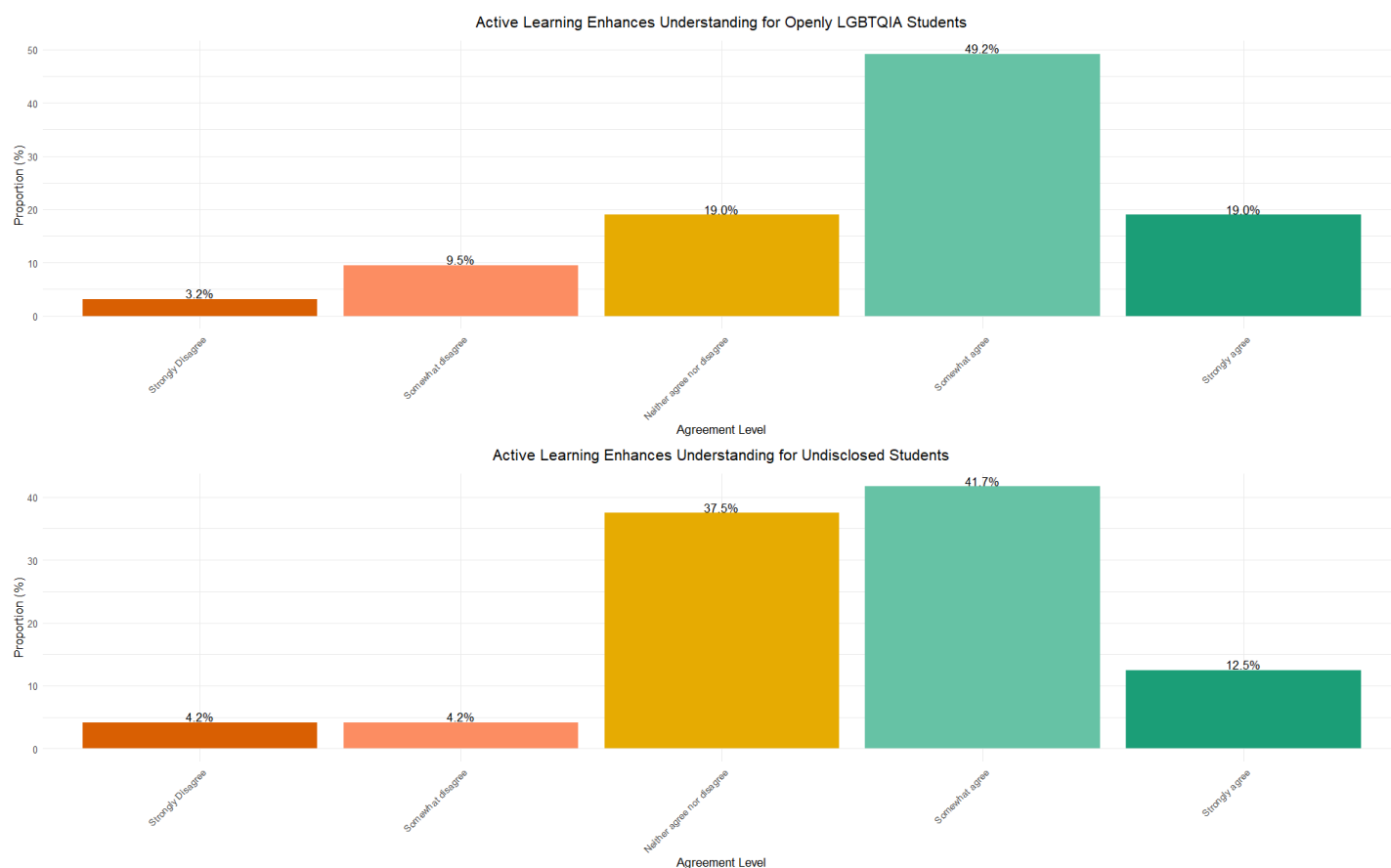


Figure 2.1: Perceived Effectiveness of Active Learning for Openly and Undisclosed LGBTQIA Students

Another important aspect is student engagement. Specifically, we aimed to determine whether our observations regarding LGBTQIA students' comfort levels in engaging with others aligned with findings

from extant literature. Figure 2.2 shows that openly LGBTQIA students reported higher comfort levels, with 36.5% somewhat agreeing and 17.5% strongly agreeing that they felt comfortable interacting in class. In contrast, undisclosed LGBTQIA students reported higher levels of discomfort, with 20.8% somewhat disagreeing and 33.3% remaining neutral. These findings are consistent with existing research, which suggests that students who are less open about their LGBTQIA identity tend to feel less comfortable participating and engaging with peers.



Figure 2.2: Comfort Levels of Openly and Undisclosed LGBTQIA Students When Engaging with Peers and Instructors

Next, we explored students' preferences for how often they would like to interact with peers during class. Figure 2.3 indicates that among the openly LGBTQIA students, the majority—44.4%—preferred engaging once per class, while 27.0% preferred multiple interactions during each class session. However, undisclosed

LGBTQIA students appeared more hesitant to interact, with 25.0% preferring engagement only once per week and another 25.0% preferring no engagement.

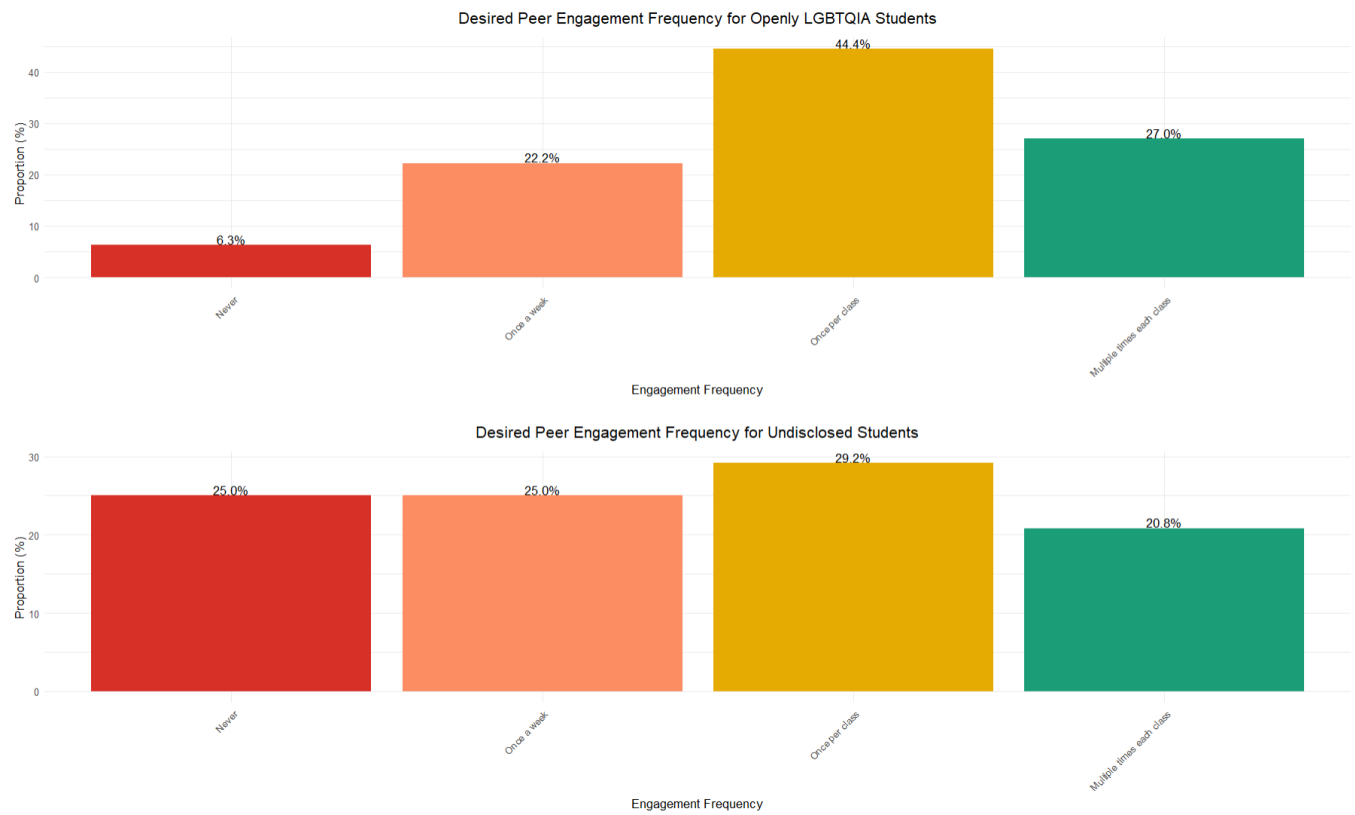


Figure 2.3: Desired Peer Engagement Frequency Among Openly and Undisclosed LGBTQIA Students

2.2.2 Comparison of Test Scores Between Active Learning and Traditional Classrooms

Next, we took a more in-depth look at the classrooms' use of active learning strategies and students' test grades. We compared the test grades of openly LGBTQIA and undisclosed LGBTQIA in active learning and traditional classrooms. For each test combination (openly vs. undisclosed), we first tested for equal variances with Levene's Test, using the **leveneTest()** function of the **car** package (Fox and Weisberg, 2019). We then conducted two-sample t-tests using **t.test()** function in Base R. All tests were conducted at significance level of 0.05 and 95% coefficients were given for confidence intervals.

First, we analyzed student performance on the first exam in classrooms with active learning versus more traditional classrooms, with results summarized in Table 2.2 presents the mean and standard deviation on the first exam by LGBTQIA identity and classroom type. The p-values from Levene's Test were 0.317 and 0.2697 for the "yes" and "maybe" LGBTQIA groups, respectively. Since both p-values are greater than 0.05, could assume equal variances and proceeded with the t-tests.

Among openly LGBTQIA students, those in active learning classrooms scored slightly higher on average (81.7) than those in traditional classrooms (80.4). However, the difference was not statistically significant, $t(61) = -0.3029, p = 0.763$. The 95% confidence interval for the mean difference was (-9.426, 6.9457). This finding suggests that while active learning may provide modest benefits, there is not evidence to conclude that it leads to substantial effect on exam performance for openly LGBTQIA students.

A similar trend was observed among for potential LGBTQIA students. Again, students in active learning classrooms had a higher average score on the first exam (84) than their counterparts in traditional classrooms (79.7). However, this difference was also not statistically significant, $t(22) = -0.8124, p = 0.4253$. The 95% confidence interval for the mean difference was (-15.0168, 6.5635). These results indicate that although students in active learning environments tended to score higher on average, the effect of classroom type did not significantly impact first exam performance for either group.

Table 2.2: Test 1 Summary Statistics

LGBTQIA Status	Active Learning	Traditional Classroom	Total
Prefer not to say	$n = 15$ Mean = 84 SD = 10.5	$n = 9$ Mean = 79.7 SD = 15	$n = 24$ Mean = 82.3 SD = 13.5
Yes	$n = 46$ Mean = 81.7 SD = 15.7	$n = 17$ Mean = 80.4 SD = 10	$n = 63$ Mean = 81.3 SD = 14.3
Total	$n = 61$ Mean = 82.2 SD = 14.6	$n = 26$ Mean = 80.2 SD = 11.7	$n = 87$ Mean = 81.6 SD = 13.7

To continue our investigation test performance trends, we examined students' average grades across the first two tests, as shown in Table 2.3. The p-values from Levene's Test were 0.1228 and 0.3394 for the "yes" and "maybe" groups, respectively. Since both p-values were greater than the significance level, we assumed equal variances and conducted t-tests.

Among openly LGBTQIA students, those in active learning classrooms had a slightly lower mean score of 155 points (77.5%), compared to 159 points (79.5%) in traditional classrooms. This difference was not statistically significant, $t(61) = 0.4263$, $p = 0.6714$, with a 95% confidence interval of $(-13.2442, 20.4212)$. These results suggest there is insufficient evidence to conclude that instructional format had a substantial effect on second exam performance.

Among undisclosed students, those in active learning classrooms had a higher average score of 163 points (81.5%), compared to 160 points (80%) in traditional classrooms. Again, the difference was not statistically significant, $t(22) = -0.3007$, $p = 0.7665$, with a 95% confidence interval of $(-23.5533, 17.8888)$. These findings suggest that active learning did not lead to a statistically substantial test performance difference for this group across two assessments.

Table 2.3: Test 2 Summary Statistics

LGBTQIA Status	Active Learning	Traditional Classroom	Total
Prefer not to say	$n = 15$ Mean = 163 SD = 19.3	$n = 9$ Mean = 160 SD = 29.4	$n = 24$ Mean = 162 SD = 23.1
Yes	$n = 46$ Mean = 155 SD = 32.9	$n = 17$ Mean = 159 SD = 17.8	$n = 63$ Mean = 156 SD = 29.5
Total	$n = 61$ Mean = 157 SD = 30.1	$n = 26$ Mean = 159 SD = 21.9	$n = 87$ Mean = 157.6 SD = 27

Next, we examined students' average test scores across the first three exams (see Table 2.4). The p -values from Levene's Test were 0.927 and 0.736 for the "yes" and "maybe" groups, respectively. Since both p -values were greater than 0.05, we assumed equal variances and conducted t -tests.

Among openly LGBTQIA students, those in active learning classrooms had a slightly lower average score of 232 points (77.3%) compared to 237 points (79.0%) in traditional classrooms. This difference was not statistically significant, $t(61) = 0.4756, p = 0.6361$, with a 95% confidence interval of $(-16.6887, 27.1034)$. Thus, we do not have enough evidence to conclude active learning had a positive effect on test performance over multiple assessments for this group.

For undisclosed students, those in active learning environments had a higher average score of 250 points (83.3%), compared to 237 points (79.0%) for students in traditional classrooms. This difference was also not statistically significant, $t(22) = -0.9537, p = 0.3506$, with a 95% confidence interval of $(-39.9982, 14.7987)$. This finding suggests that there is not enough evidence that active learning techniques did result in notable differences in performance over three exams between students in active learning vs. traditional classrooms.

Table 2.4: Test 3 Summary Statistics

LGBTQIA Status	Active Learning	Traditional Classroom	Total
Prefer not to say	$n = 15$ Mean = 250 SD = 21.7	$n = 9$ Mean = 237 SD = 43.3	$n = 24$ Mean = 245 SD = 31.3
Yes	$n = 46$ Mean = 232 SD = 42.1	$n = 17$ Mean = 237 SD = 26.4	$n = 63$ Mean = 234 SD = 38.3
Total	$n = 61$ Mean = 236 SD = 38.7	$n = 26$ Mean = 237 SD = 32.3	$n = 87$ Mean = 236.8 SD = 36.7

Finally, we examined students' test averages from all exams (see Table 2.5). The p-values from Levene's Test were 0.0557 and 0.0928 for the "yes" and "maybe" groups, respectively. Since both p-values were greater than 0.05, we assumed equal variances and conducted t-test.

Among openly LGBTQIA students, those in active learning classrooms had an average score of 300 points (75%), while those in traditional classrooms averaged 312 points (78%). However, this difference was not statistically significant, $t(61) = 0.8872, p = 0.3784$, with a 95% confidence interval of $(-14.9876, 38.8962)$. This finding suggests that we do not have enough evidence to conclude active learning led to a considerable improvement in performance on all exams.

For students who preferred not to disclose their LGBTQIA status, those in active learning classrooms had a higher mean score of 325 points (81.3%), compared to 311 points (77.8%) in traditional classrooms. Although the active learning group scored slightly higher, the difference was not statistically significant, $t(22) = -0.7972, p = 0.4339$, with a 95% confidence interval of $(-51.8506, 23.0564)$.

Table 2.5: Test 4 Summary Statistics

LGBTQIA Status	Active Learning	Traditional Classroom	Total
Prefer not to say	$n = 15$ Mean = 325 SD = 32.5	$n = 9$ Mean = 311 SD = 56.6	$n = 24$ Mean = 320 SD = 42.5
Yes	$n = 46$ Mean = 300 SD = 51.7	$n = 17$ Mean = 312 SD = 32.6	$n = 63$ Mean = 303 SD = 47.4
Total	$n = 61$ Mean = 306 SD = 48.7	$n = 26$ Mean = 312 SD = 41.3	$n = 87$ Mean = 307.7 SD = 46.5

Although conducting two sample t-tests provided information into general trends regarding student test performances and active learning classroom status for both “yes” and “maybe” LGBTQIA groups, none of the trends were statistically significant. This suggests that test scores may be influenced by other factors beyond pedagogical practices alone. To better understand how active learning influences students’ performance and classroom experiences, we must account for potential confounding variables. These may include race, disability status, transfer status, and others. Thus, we utilize regression modeling techniques, which would allow us to explore these relationships more rigorously.

2.3 Methodological Framework

This thesis examines the implementation of active learning techniques to examine differences in students’ test performance, with a particular focus on LGBTQIA status and classroom structure. As in previous analyses, we classify students into two groups based on their self-identified LGBTQIA status: “Yes” and “Maybe.” We first fitted separate multiple linear regression models for each group, followed by a combined model using data from both groups.

2.3.1 Multiple Linear Regression

To begin our analysis, we fit multiple linear regression models to predict the total test scores (out of 400 points) for both of the aforementioned groups. The multiple regression models were fitted using the **lm()** function in **stats** package (R Core Team, 2023b). In particular, for the openly LGBTQIA students group, the model equation is

$$\begin{aligned} \text{TotalTestGrade}_i = & \beta_0 + \beta_1 \cdot I_{(\text{ActiveLearningSection})} + \beta_2 \cdot \text{HouseholdIncome}_i \\ & + \beta_3 \cdot \text{ResidenceType}_i + \beta_4 \cdot \text{Race}_i \\ & + \beta_5 \cdot \text{DRCRegistration}_i + \varepsilon_i. \end{aligned} \quad (2.1)$$

Also, the model for undisclosed student group is

$$\begin{aligned} \text{TotalTestGrade}_i = & \beta_0 + \beta_1 \cdot I_{\text{ActiveLearningSection}} + \beta_2 \cdot \text{HouseholdIncome}_i \\ & + \beta_3 \cdot \text{ResidenceType}_i + \beta_4 \cdot \text{Race}_i \\ & + \beta_5 \cdot \text{DRCRegistration}_i + \varepsilon_i. \end{aligned} \quad (2.2)$$

Finally, the model for students in both groups is

$$\begin{aligned} \text{TotalTestGrade}_i = & \beta_0 + \beta_1 \cdot I_{\text{ActiveLearningSection}_i} + \beta_2 \cdot \text{HouseholdIncome}_i \\ & + \beta_3 \cdot \text{Race}_i + \beta_4 \cdot \text{TransferStatus}_i + \beta_5 \cdot \text{Sex}_i \\ & + \beta_6 \cdot \text{CurrentAge}_i + \beta_7 \cdot \text{DRCRegistration}_i + \varepsilon_i. \end{aligned} \quad (2.3)$$

For all models, the subscript i denotes the i^{th} student in the dataset. Moreover, $I_{(\text{ActiveLearningSection})}$ is an indicator for whether the student was enrolled in an active learning section. Mathematically, it is defined by

$$I_{\text{ActiveLearningSection}} = \begin{cases} 1, & \text{if student is in an Active Learning section} \\ 0, & \text{if student is in a Traditional section.} \end{cases}$$

In addition, the conditions for independence, normality, and homoscedasticity were checked and met. After verifying the assumptions, we applied a backward stepwise variable selection to identify relevant predictors of students' test grades. The final model in each case was selected based on the lowest Akaike Information Criterion (AIC) value. Furthermore, to assess multicollinearity and model fit, we calculated variance inflation factors (VIFs) for each variable in equations (2.1), (2.2), and (2.3). Then, we evaluated model performance using both R^2 and adjusted R^2 values.

2.3.2 Multinomial Logistic Regression

To further explore variation in students' test scores, we categorized performance levels into three ordinal groups based on students' cumulative test grades. Specifically, we transformed the continuous variable **TotalTestGrade** into three ordinal categories representing score ranges, 0–72.5, 72.5–82.3, and 82.3–100. These categories were chosen to approximate meaningful performance levels and were labeled Low, Medium, and High, as shown in Table 2.6. These cutoffs were selected to reflect broader patterns in student performance for clearer interpretation of performance levels.

Table 2.6: Ordinal Levels of Test Performance

New Response	Old Response	Performance Level
1	0–72.5	Low
2	72.5–82.3	Medium
3	82.3–100	High

Next, we assessed whether students' performance levels varied based on learning environment and demographic characteristics, we fitted a multinomial logistic regression model. Specifically, we used the **multinom()** function from **nnet** package (Venables and Ripley, 2002). This approach allows us to model the probability of a student falling into a particular performance category, given their demographic profile and classroom setting. The model uses "Low" as the reference point, so improvements or declines in test performance are more clearly interpreted. In particular, the model is defined as

$$\begin{aligned}
\log \left(\frac{P(Y = j)}{P(Y = k)} \right) = & \beta_{j0} + \beta_{j1} \cdot I_{(\text{ActiveLearningSection})} + \beta_{j2} \cdot \text{HouseholdIncome}_i \\
& + \beta_{j3} \cdot \text{ParentEducation}_i + \beta_{j4} \cdot \text{Race}_i \\
& + \beta_{j5} \cdot \text{TransferStatus}_i + \beta_{j6} \cdot \text{DRCRegistration}_i,
\end{aligned} \tag{2.4}$$

where $j = 2, 3$ and $k = 1$.

We then used the **Anova()** function from the **car** package to assess the statistical significance of predictors in the model.

2.3.3 Mixed Effects Model

To account for differences in classroom settings, we fit we fit a linear mixed-effects model using the **lmer()** function from the **lme4** package (Bates et al., 2015). Specifically, we fit a random intercept model in which the instructor of record was included as a random effect. Recall that in Spring 2024, four different instructors taught STAT 2000. To account for this, we grouped the course sections by CRN and created a new variable, **Instructor**, to indicate which lab sections were linked to the large lecture hall class. We chose to use **Instructor** as the grouping variable for the random effect rather than CRN, as there were only four instructors compared to 36 unique CRNs. In other words, the intercept (i.e. baseline of test performance) was allowed to vary by instructor. All other available predictors were treated as fixed effects. In particular, the random intercepts model is given as

$$\begin{aligned}
\text{TotalTestGrade}_{ij} = & \beta_0 + \beta_1 \cdot \text{ActiveLearningSection}_{ij} + \beta_2 \cdot \text{Race}_{ij} + \beta_3 \cdot \text{Sex}_{ij} \\
& + \beta_4 \cdot \text{CurrentAge}_{ij} + \beta_5 \cdot \text{ResidenceType}_{ij} \\
& + \beta_6 \cdot \text{DRCRegistration}_{ij} + \mu_j + \epsilon_{ij},
\end{aligned} \tag{2.5}$$

where

- i indexes students within each classroom section;
- j indexes instructors;

- $\mu_j \sim \mathcal{N}(0, \sigma_\mu^2)$ is the random intercept for classroom j ;
- $\varepsilon_{ij} \sim \mathcal{N}(0, \sigma^2)$ is the residual error for student i in instructor j 's class.

The variance–covariance formulation of the random intercept model is given by

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{\mu} + \boldsymbol{\varepsilon},$$

where

- $\mathbf{y}$ is an $n \times 1$ vector of students' test grades, with n representing the total number of students;
- $\mathbf{X}$ is an $n \times p$ design matrix for the fixed effects;
- $\boldsymbol{\beta}$ is a $p \times 1$ vector of fixed-effect coefficients;
- $\mathbf{Z}$ is an $n \times q$ design matrix for the random effects;
- $\boldsymbol{\mu} \sim \mathcal{N}(0, \mathbf{G})$ is a $q \times 1$ vector of random effects;
- $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \mathbf{R})$ is the $n \times 1$ vector of residuals.

Then, the variance of $\mathbf{y}$ is denoted as

$$\text{Var}(\mathbf{y}) = \mathbf{Z}\mathbf{G}\mathbf{Z}' + \mathbf{R},$$

where

- $\mathbf{Z} \in \mathbb{R}^{n \times q}$, where n is the number of students and q is the levels of instructors (4 in this case);
- $\mathbf{G} \in \mathbb{R}^{q \times q}$, the covariance matrix, where the diagonal elements are the variance of the random intercepts (instructors);
- $\mathbf{R} = \sigma^2 \mathbf{I}_n$ is an $n \times n$ diagonal matrix of residuals.

Next, we explored whether the relationship between a predictor and test performance might also vary across classroom types. Specifically, we fit a random slope model with a fixed intercept across classrooms (i.e., holding baseline test performance constant), but the slope for a specific predictor was allowed to vary depending whether students were in active or traditional classrooms. Here, we modeled **CurrentAge** as a random slope, allowing its relationship with test performance to vary across instructors. This specification yielded the lowest AIC value. The form of the model is

$$\begin{aligned} \text{TotalTestGrade}_{ij} = & \beta_0 + \beta_1 \cdot \text{ActiveLearningSection}_{ij} + \beta_2 \cdot \text{Race}_{ij} + \beta_3 \cdot \text{Sex}_{ij} \\ & + \beta_4 \cdot \text{CurrentAge}_{ij} + \beta_5 \cdot \text{ResidenceType}_{ij} \\ & + \beta_6 \cdot \text{DRCRegistration}_{ij} + b_j \cdot \text{CurrentAge}_{ij} + \varepsilon_{ij}, \end{aligned} \quad (2.6)$$

where

- i indexes students within each classroom section;
- j indexes instructors;
- $b_j \sim \mathcal{N}(0, \sigma_b^2)$ is the random slope for **CurrentAge** in instructor j 's class;
- $\varepsilon_{ij} \sim \mathcal{N}(0, \sigma^2)$ is the residual error for student i in instructor j 's class.

The random slope only model is also denoted as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{b} + \boldsymbol{\varepsilon},$$

where

- $\mathbf{y}$ is an $n \times 1$ vector of students' test grades, with n representing the total number of students;
- $\mathbf{X}$ is an $n \times p$ design matrix for the fixed effects;
- $\boldsymbol{\beta}$ is a $p \times 1$ vector of fixed-effect coefficients;

- $\mathbf{Z}$ is an $n \times q$ design matrix for **CurrentAge**;
- $\mathbf{b} \sim \mathcal{N}(0, \mathbf{G})$, where $\mathbf{G} \in \mathbb{R}^{q \times q}$ is the covariance matrix of random slopes;
- $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \mathbf{R})$ is the $n \times 1$ vector of residuals.

Then the variance of $\mathbf{y}$ is

$$\text{Var}(\mathbf{y}) = \mathbf{ZGZ}^\top + \mathbf{R},$$

where

- $\mathbf{Z} \in \mathbb{R}^{n \times q}$ is the random slope matrix, with q representing the number of instructors;
- $\mathbf{G} \in \mathbb{R}^{q \times q}$ is the covariance matrix, where the diagonal elements are the variance of the random slope (age);
- $\mathbf{R} = \sigma^2 \mathbf{I}_n$ is an $n \times n$ diagonal matrix of residuals.

To continue our exploration on how the relationship between student age and test performance might differ across classroom types, we fit a linear mixed model with both a random intercept for **Instructor** and a random slope for **CurrentAge**. In this case, both the baseline level of test performance and the effect of student age were allowed to differ between instructors' sections. This model is written as

$$\begin{aligned} \text{TotalTestGrade}_{ij} = & \beta_0 + \beta_1 \cdot \text{ActiveLearningSection}_{ij} + \beta_2 \cdot \text{Race}_{ij} + \beta_3 \cdot \text{Sex}_{ij} \\ & + \beta_4 \cdot \text{CurrentAge}_{ij} + \beta_5 \cdot \text{ResidenceType}_{ij} \\ & + \beta_6 \cdot \text{DRCRegistration}_{ij} + \mu_j + b_j \cdot \text{CurrentAge}_{ij} + \varepsilon_{ij}, \end{aligned} \quad (2.7)$$

where

- i indexes students within each classroom section;
- j indexes instructors;

- $\mu_j \sim \mathcal{N}(0, \sigma_\mu^2)$ is the random intercept for instructor j 's class;
- $\varepsilon_{ij} \sim \mathcal{N}(0, \sigma^2)$ is the residual error for student i in instructor j 's class.

The random intercept and slope model can be written as

$$y = X\boldsymbol{\beta} + Z\mathbf{b} + \boldsymbol{\varepsilon},$$

where

- $\mathbf{y}$ is an $n \times 1$ vector of students' test grades, with n representing the total number of students;
- $\mathbf{X}$ is an $n \times p$ design matrix for the fixed effects;
- $\boldsymbol{\beta}$ is a $p \times 1$ vector of fixed-effect coefficients;
- $\mathbf{Z}$ is an $n \times 2q$ design matrix for random intercept and slopes, with q being the number of instructors;
- $\mathbf{b} \sim \mathcal{N}(0, \mathbf{G})$, where $\mathbf{G} \in \mathbb{R}^{2q \times 2q}$ is the covariance matrix of random intercepts and slopes;
- $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \mathbf{R})$ is the $n \times 1$ vector of residuals.

The variance of $\mathbf{y}$ is given by

$$\text{Var}(\mathbf{y}) = \mathbf{ZGZ}^\top + \mathbf{R},$$

where

- $\mathbf{Z} \in \mathbb{R}^{n \times 2q}$ since student contributes to two random effects, random intercept and random slope of **CurrentAge**;
- $\mathbf{G} \in \mathbb{R}^{2q \times 2q}$ is a block diagonal matrix consisting of the variances and covariances of the random intercepts and random slopes (for **CurrentAge**) across all q instructors.
- $\mathbf{R} = \sigma^2 \mathbf{I}_n \in \mathbb{R}^{n \times n}$ is the residual variance matrix.

Together, these approaches allowed us to examine both overall trends and nuanced differences in students' test performance across learning environments and between openly LGBTQIA and undisclosed student groups. By employing multiple models, we gained a more nuanced understanding of the factors that may influence students' test performance.

CHAPTER 3

RESULTS

3.1 Multiple Linear Regression

The results of the multiple linear regression models for predicting total test scores are summarized Table ?? and Table 3.3 for the openly LGBTQIA students and students who preferred not to disclose, respectively. The overall model fit statistics for each groups are presented in Tables 3.2 and 3.4.

The model that aimed to predict test grades for the openly LGBTQIA group explained approximately 55.4% of the variance in test scores ($R^2 = 0.5535$, Adjusted $R^2 = 0.4572$). The overall model was statistically significant ($F(11, 51) = 5.748, p < 0.0001$). According to the Ordinary Least Squares (OLS) model, among the predictors, **TransferStatus** **DRCRegistration**, and **SexMale** were statistically significant predictors of **TotalTestGrade**. Specifically, students who transferred scored, on average, 36.843 points lower (roughly 9.21%) than those who did not transfer ($p = 0.0027$). Students who registered with the DRC scored, on average, 33.324 points lower (or approximately 8.33%) than those who did not ($p = 0.0237$). Male students scored 36.06 points higher (roughly 9.02%) than female students ($p = 0.0345$).

In contrast, predictors such as **SexOther**, and **ActiveLearningSection** were not statistically significant. On average, students who identified as other sex scored 20.806 points higher (approximately 5.20%) than female students ($p = 0.4250$). When assessing the relationship between students' test grades in

active learning classrooms versus those in traditional settings, active learning was not a statistically significant predictor ($p = 0.4522$). These findings indicate that there is not enough evidence to conclude that active learning improves test performance for openly LGBTQIA students

Table 3.1: Regression Coefficients of Model Predicting Total Test Grades for Openly LGBTQIA Students

Variable	Estimate	Standard Error	T-value	P-value
Intercept	504.643	66.230	7.620	<0.0001
ActiveLearningSectionNo	7.842	10.351	0.758	0.4522
HouseholdIncome\$0–\$30,000	-77.928	43.862	-1.777	0.0816
HouseholdIncome\$30,001–\$48,000	-48.607	17.823	-2.727	0.0088
HouseholdIncome\$48,001–\$75,000	-20.367	12.203	-1.669	0.1013
HouseholdIncome\$75,001–\$110,000	-14.261	19.817	-0.720	0.4747
TransferStatusYes	-36.843	11.702	-3.148	0.0027
CurrentAge	-9.057	3.473	-2.608	0.0119
SexMale	36.063	16.601	2.172	0.0345
SexOther	20.806	25.874	0.804	0.4250
DRCRegistrationYes	-33.324	14.296	-2.331	0.0237

Table 3.2: Summary Statistics of Model Predicting Total Test Grades for Openly LGBTQIA Students

Statistic	Value
Residual Standard Error	34.91
Multiple R-squared	0.5535
Adjusted R-squared	0.4572
F-statistic	5.748
p-value	<0.0001

The model for students who did not disclose their LGBTQIA status accounted for approximately 68.9 % of the variation in test scores ($R^2 = 0.6893$, Adjusted $R^2 = 0.4045$). The overall model was not statistically significant ($F(11, 12) = 2.42$, $p = 0.0721$). According to the OLS model, the only statistically significant predictors of test grades were students identifying as Black or African American and students coming from families that earned an income of \$30,001–\$48,000. Specifically, students identifying as Black or African American scored, on average, 112.67 points lower (approximately 28.17%) than White students ($p = 0.0019$). In contrast, students in the \$30,001–\$48,000 income bracket scored, on average, 105.94 (approximately 26.49%) points higher than those in the \$48,001–\$75,000 income bracket ($p = 0.0142$).

Insignificant predictors included **ActiveLearningSection**, **ResidenceType**, and other income and racial categories. For example, students from rural areas scored, on average, 50.9421 points (about 12.74%) lower than those from suburban areas ($p = 0.1330$). Moreover, on average, students in active learning sections scored 0.9725 points lower (approximately 0.24%) than those in traditional sections ($p = 0.9495$). These findings indicate that there is not enough evidence to conclude that active learning improves test performance for openly LGBTQIA students.

Table 3.3: Regression Coefficients of Model Predicting Total Test Grades for Undisclosed Students

Variable	Estimate	Standard Error	T-value	P-value
Intercept	315.4357	18.2778	17.258	<0.0001
ActiveLearningSectionNo	-0.9725	15.0250	-0.065	0.9495
HouseholdIncome\$0-\$30,000	8.1971	32.4539	0.253	0.8049
HouseholdIncome\$30,001-\$48,000	105.9363	36.9841	2.864	0.0142
HouseholdIncome\$75,001-\$110,000	20.8769	21.1008	0.989	0.3420
HouseholdIncome> \$110,000	20.0691	22.8787	0.877	0.3976
ResidenceTypeRural	-50.9421	31.6068	-1.612	0.1330
ResidenceTypeUrban	6.1739	23.8241	0.259	0.7999
RaceAsian	17.2886	25.5054	0.736	0.4762
RaceBlack or African American	-112.6694	28.4236	-3.964	0.0019
RaceHispanic or Latino	-19.5893	22.7352	-0.862	0.4058
DRCRegistrationYes	13.5643	37.5401	0.361	0.7241

Table 3.4: Summary Statistics of Model Predicting Total Test Grades for Undisclosed Students

Statistic	Value
Residual Standard Error	32.79
Multiple R-squared	0.6893
Adjusted R-squared	0.4045
F-statistic	2.42
p-value	0.0721

Since active learning was not a statistically significant predictor of **TotalTestGrade** in either the openly LGBTQIA group or the undisclosed group, we fitted a combined multiple regression model using both groups. The results of this regression are given in Table 3.5, and the summary statistics are provided in Table 3.6. The combined model accounted for 48.3% of the variation in test scores ($R^2 = 0.483$, Adjusted $R^2 = 0.3824$) and was statistically significant overall ($F(14, 72) = 4.804, p < 0.0001$).

According to the OLS model, predictors like **TransferStatus**, students identifying as Black or African American, male students, and **DRCRegistration** were statistically significant. For instance, students who transferred scored on average 34.025 points lower (8.51%) than those who did not transfer ($p = 0.0029$). In another case, students identifying as Black or African American scored 44.813 points lower (approximately 11.20%) than White students ($p = 0.0097$). Male students scored, on average, 30.94 points higher (about 77.4%) than female students ($p = 0.0283$). Finally, students who registered with the DRC scored, on average, 31.085 points lower (7.77%) than those who did not ($p = 0.0318$).

Predictors—including **HouseholdIncome**, **CurrentAge**, and other sex and racial identities—were statistically insignificant in this model. Active learning remained a non-significant predictor ($p = 0.7024$). This suggests that there is not enough evidence to conclude that students in active learning classrooms performed significantly differently from those in traditional sections across these groups.

Table 3.5: Regression Coefficients of Model Predicting Total Test Grades for Both Groups

Variable	Estimate	Standard Error	T-value	P-value
Intercept	428.202	60.461	7.082	<0.0001
ActiveLearningSectionNo	3.463	9.028	0.384	0.7024
HouseholdIncome\$0–\$30,000	-29.938	24.212	-1.236	0.2203
HouseholdIncome\$30,001–\$48,000	-30.627	16.121	-1.900	0.0615
HouseholdIncome\$48,001–\$75,000	-3.713	11.155	-0.333	0.7402
HouseholdIncome\$75,001–\$110,000	-3.544	10.273	-0.345	0.7311
RaceAsian	25.187	13.080	1.926	0.0581
RaceBlack or African American	-44.813	16.859	-2.658	0.0097
RaceHispanic or Latino	-4.659	18.016	-0.259	0.7967
TransferStatusYes	-34.025	11.053	-3.078	0.0029
CurrentAge	-5.455	3.187	-1.712	0.0912
SexMale	30.940	13.821	2.239	0.0283
SexOther	1.691	18.783	0.090	0.9285
DRCRegistrationYes	-31.085	14.194	-2.190	0.0318

Table 3.6: Summary Statistics of Model Predicting Total Test Grades for Both Groups

Statistic	Value
Residual Standard Error	36.52
Multiple R-squared	0.483
Adjusted R-squared	0.3824
F-statistic	4.804
p-value	<0.0001

3.2 Multinomial Logistic Regression

A multinomial logistic regression model was employed to investigate the relationship between students' test performance levels (Low, Medium, High) and their learning context, with the Low performance level serving as the reference category. The results of the multinomial logistic regression are presented in Table 3.7. In particular, the model estimated the log-odds of students scoring in the Medium or High score range relative to scoring the Low range.

Table 3.7: Multinomial Logistic Regression Coefficients and Standard Errors by Performance Group

Group	Coefficients		Standard Errors	
	(Intercept)	ActiveLearningSectionNo	(Intercept)	ActiveLearningSectionNo
Medium	0.412	0.905	0.668	0.704
High	1.045	0.753	0.663	0.802
		Residual Deviance: 136.917	AIC: 188.917	

The coefficient for **ActiveLearningSection** for the Medium performance group (compared to the Low performance group) was not statistically significant ($p = 0.5372$). Similarly, the coefficient for **ActiveLearningSection** in the High group (compared to lower) was also not statistically significant ($p = 0.1152$). These findings indicate enrollment in active learning classrooms did not significantly affect the odds of students scoring in the Medium or High test performance range relative to those in the Low range.

Table 3.8 presents odds ratios for performance group comparisons. The estimated odds ratio between the Medium and Low performance groups was 2.472, with a 95% confidence interval of (0.622, 9.834). This

suggests that students enrolled in active learning sections had approximately 1.8 times the odds of scoring in the Medium performance range compared to those in traditional sections. For the High performance group, the odds ratio was 2.124, with a 95% confidence interval of (0.441, 10.235). These findings suggest that students in traditional classrooms had higher odds of scoring in the Medium or High performance categories compared to those in active learning sections. However, neither effect was statistically significant, so we do not have enough evidence conclude there is a substantial difference in test performance based on classroom type.

Table 3.8: Odds Ratios by Performance Group

	(Intercept)	ActiveLearningSectionNo
Medium	1.511	2.472
High	2.842	2.124

Table 3.9 summarizes the significance of each predictor in the multinomial logistic regression model comparing performance levels. The variable **ActiveLearningSection** was not found to be statistically significant in the performance group model ($\chi^2(2) = 1.8227, p = 0.4020$). **HouseholdIncome** was also not statistically significant in this model ($\chi^2(10) = 9.3214, p = 0.5026$). Several other predictors were statistically significant. These included **ParentEducation** ($\chi^2(2) = 9.8457, p = 0.0073$), **Race** ($\chi^2(6) = 20.1258, p = 0.0026$), **TransferStatus** ($\chi^2(2) = 13.0600, p = 0.0015$), and **DRCRegistration** ($\chi^2(2) = 6.1197, p = 0.0469$).

Table 3.9: Effects of Terms in the Model Comparing Among Performance Groups

Term	Df	χ^2	P-value
ActiveLearningSection	2	1.8227	0.4020
HouseholdIncome	10	9.3140	0.5026
ParentEducation	2	9.8457	0.0073
Race	6	20.1258	0.0026
TransferStatus	2	13.0600	0.0015
DRCRegistration	2	6.1197	0.0469

3.3 Mixed Effects Model

To compare students' grades across classroom sections, we fit three linear mixed-effects models. The first was a random intercept model, where the instructor of record was treated as a random intercept. The fixed effects included **ActiveLearningSection**, **Race**, **Sex**, **CurrentAge**, **ResidenceType**, and **DRCRegistration**. Several of these were found to be statistically significant, as their confidence intervals do not include 0 (see Figure 3.1). For example, students identifying as Black or African American scored on average 46.19 points lower (approximately 11.55%) compared to Whites. **CurrentAge** was a significant predictor, with older students scoring 11.25 points lower (about 28.13%) on average. **DRCRegistration** was also statistically significant, with registered students scoring on average 28.71 points lower (about 7.18%) than those who did not register.

In contrast, predictors such as **ActiveLearningSection**, **Sex**, and **ResidenceType** were not statistically significant, as their confidence intervals included zero. The random effect for **Instructor** had a variance of 1644 and a standard deviation of 40.54, which indicates a moderate variability in scores across instructors.

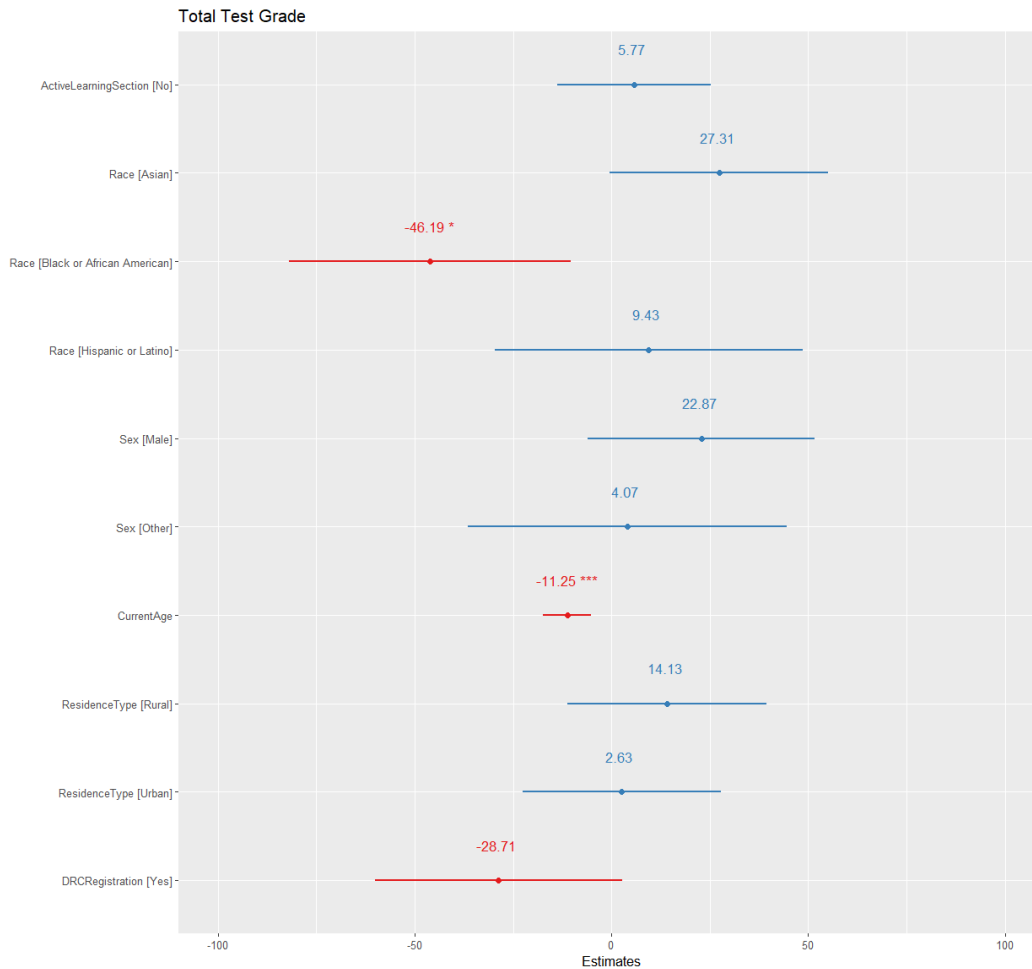


Figure 3.1: Confidence Intervals for Model Estimates in Random Intercepts Model

Next, we examined whether the relationship between student age and test performance differed across instructors' sections. To do this, we fit a random slope model in which the intercept (i.e., baseline line level of test performance) was fixed across classrooms, but the slope for a specific predictor varied depending on which instructor the student had. Specifically, we treated **CurrentAge** as the random effect, while all other predictors were held fixed. We also fit a model with both a random slope and a random intercept. However, we chose to report results from the random slope model only, as adding a random intercept may risk overfitting, and both models shared the same lowest AIC value.

According to Figure 3.2, Black or African American students and **DRCRegistration** were significant predictors, as their confidence intervals do not contain zero. For instance, Black or African American

students scored, on average, 49.42 points lower (approximately 12.36%) than White students. Additionally, students who were registered with the DRC also scored, on average, 40.15 points lower (about 10.04%) than those without accommodations.

All other predictors were not statistically significant, as their confidence intervals included zero. A couple statistically insignificant predictors include **ResidenceType** and **ActiveLearningSection**. For instance, students from rural areas had a higher average score ($\beta = 13.75$) compared to those from suburban. In addition, students in traditional classrooms had slightly higher performance ($\beta = 5.47$) than those in than those in active learning classrooms.

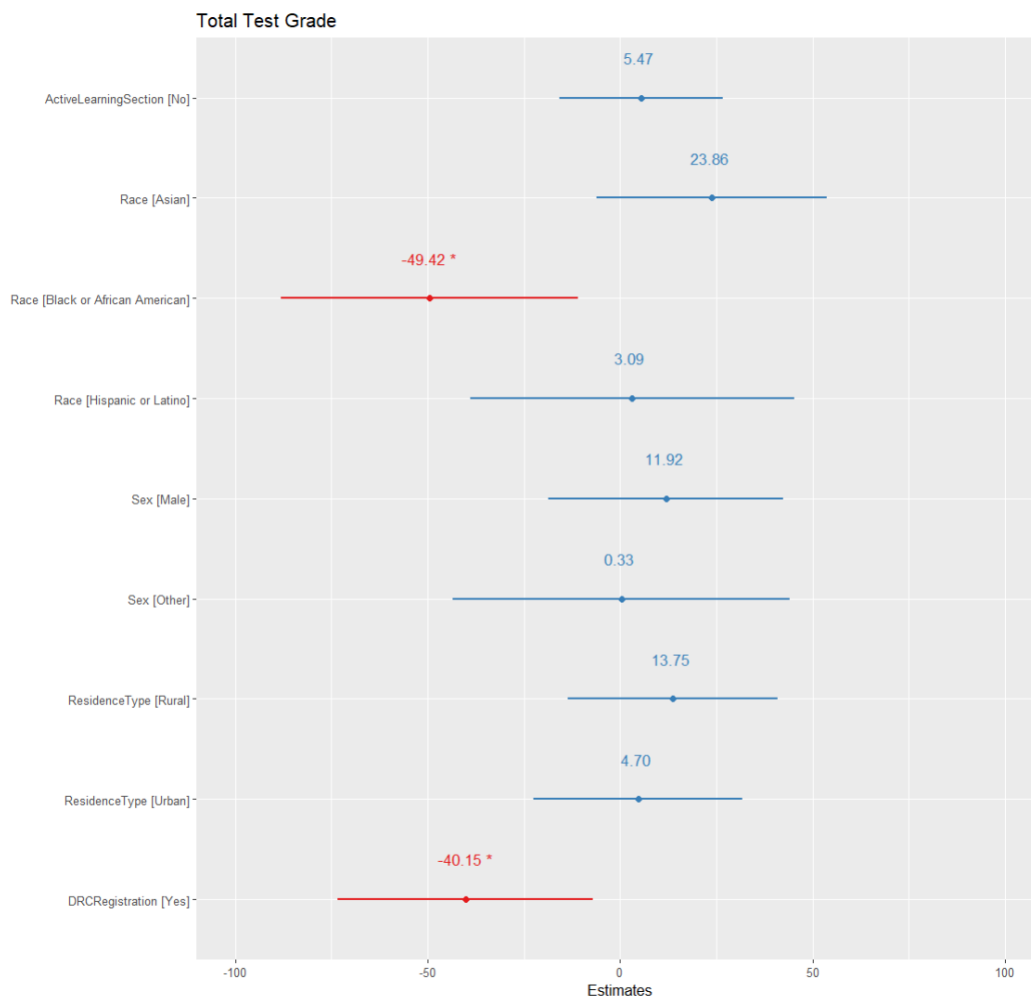


Figure 3.2: Confidence Intervals for Model Estimates in Random Slopes

CHAPTER 4

DISCUSSION

To evaluate the effectiveness of active learning for LGBTQIA students in STAT 2000 during Spring 2024, we used students' cumulative test scores as the primary measure of academic performance. Drawing from the results of our models, we found that active learning did not significantly influence test performance for openly LGBTQIA students, those who preferred not to disclose their identities, or the combined group. Based on these findings, we expanded the analysis to include all 618 students who consented to participate. There, we found that active learning did not significantly improve test scores. Overall, the fact that active learning was not a significant predictor of test performance may reflect underlying challenges LGBTQIA students face in such environments, as described in prior literature.

4.1 Limitations and Future Work

While this study yielded several important findings, it is not without limitations. First, because our focus was on definite or possible LGBTQIA students, the sample size was limited. Similarly, there was an imbalance in classroom representation, with more students enrolled in active learning sections (61) than in traditional lecture sections (27). This uneven distribution may have limited our ability to draw strong comparisons between the two formats. Second, the data were drawn from a single semester—the first term that active learning was newly implemented. At that time, instructors and students may still have

been adjusting to the format. Third, because instructors likely had varying teaching styles, we were unable to measure how consistently active learning was implemented across classrooms.

Since this study remains in progress, it is useful to offer several recommendations to guide future work. First, we should aim for a more balanced distribution of students across traditional and active learning sections to improve group comparability. Second, with continued data collection and refinement in pedagogy, it is possible that active learning will emerge as a significant predictor of student performance. If so, future analyses may reveal that active learning significantly influences test performance for both openly LGBTQIA students and those who prefer not to disclose their identities. Finally, we plan to broaden the scope of our work by examining how active learning affects the experiences and outcomes of other student populations:

- Addressing Equity and Measuring the Impact of Active Learning: A Case Study in Large Lecture Statistics Courses
- Accommodating Students with Disabilities
- Racial Hierarchy within Active Learning Environment
- Transfer Students
- Income Inequalities and First Generation
- Men and Women
- Rural vs. Urban

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APPENDIX A: DATA DICTIONARY

Participation: Indicates whether the student agreed to participate in the study

- *Choices:* Yes, I agree to participate in the study, No, I do not wish to participate in the study.

Educational Background Variables

YearStarted: The year the student first attended college.

StatsBackground: The highest level of statistics the student has completed.

- *Choices:* I have not taken a statistics course prior to STAT2000, Statistics in high school (AP or otherwise), Introductory-level statistics in college.

MathBackground: The highest level of mathematics the student has completed.

- *Choices:* Algebra, Pre-calculus, Calculus I (Derivative calculus), Calculus II (Integral calculus), Higher than Calculus II.

PreviousCourses: A list of courses the student has taken before this study.

- *Choices:* Chemistry, Biology and/or Genetics, Introductory Physics (Mechanics and/or Electricity, etc.), Microeconomics and/or Macroeconomics, Introduction to Computing/Introductory Computer Science, Any engineering class.

TransferStatus: Indicates whether the student transferred to the University of Georgia.

- *Choices:* I did not transfer to UGA., I transferred to UGA this academic year., I transferred to UGA in a prior academic year.

GapYears: The number of years the student took off between high school and starting college.

HighSchoolZIP: The ZIP code of the high school the student attended.

Active Learning Variables

ActiveLearningSection: Indicates which section of the STAT 2000 course the student was enrolled in, used to determine whether the student experienced active learning.

- *Choices:* 57291, 57324, 57327, 57329, 57330, 57332, 57333, 57337, 57345, 57347, 64852, 64855, 64856, 64857, 64858, 64881, 64882, 64884, 64885, 64886, 64904, 64905, 64906, 61907, 64909, 64911, 649914, 64916, 64917, 64918, 57296, 64861, 64863, 64864, 64870, 64873

ActiveLearningTechniquesCombined: Types of active learning techniques experienced by the respondent.

- *Choices:* Think-Pair-Share, Small group problem-solving, Peer instruction, Case studies, Concept mapping, Role-playing, Polling, Minute Papers, Purposeful Pause, Think-Aloud, Gallery Walk, I have not encountered active learning in the course

ActiveLearningSatisfaction: The student's satisfaction with active learning experiences.

- *Choices:* Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree

ActiveLearningEnhanced: Whether active learning improved the student's understanding compared to traditional lecture styles.

- *Choices:* Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree

ComfortEngagingPeersInstructors: The student's comfort level with engaging peers and instructors in active learning settings.

- *Choices:* Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree

ImpactLearning: The extent to which active learning improved the student's overall learning experience.

- *Choices:* No/minimal effect, Slightly hindered, Helped, Strongly helped

ImpactAcquisition: How active learning affected the student's ability to acquire knowledge or skills

- *Choices:* No/minimal effect, Slightly hindered, Helped, Strongly helped

ImpactThinkCritically: The influence of active learning on the student's ability to think critically.

- *Choices:* No/minimal effect, Slightly hindered, Helped, Strongly helped

ImpactRetention: Whether active learning helped the student retain information better.

- *Choices:* No/minimal effect, Slightly hindered, Helped, Strongly helped

ImpactApplication: The extent to which active learning improved the student's ability to apply learned concepts in practical situations.

- *Choices:* No/minimal effect, Slightly hindered, Helped, Strongly helped

RecentSTEMEngagementFrequency: How frequently the student has engaged in STEM-related activities recently.

- *Choices:* Never, This is my first large STEM class, Once per week, Once per class, Multiple times each class

PeerEngagementPreferenceSTEM: The student's preference for engaging with peers during STEM-related activities or coursework.

- *Choices:* Never, Once per week, Once per class, Multiple times each class

PreferTraditional: Indicates if the student prefers traditional lecture-based teaching styles.

- *Choices:* Strongly disagree, Disagree, Neutral, Agree, Strongly agree

PreferActive: Indicates if the student prefers active teaching styles involving interaction and participation.

- *Choices:* Strongly disagree, Disagree, Neutral, Agree, Strongly agree

ActiveAlignWithLearningStyle: Whether active learning aligns with the student's personal learning style.

- *Choices:* No, Unsure, Yes

ActiveLearningCatered: Whether active learning conflicts with the student's preferred or natural learning style.

- *Choices:* No, Unsure, Yes

Sociodemographic Background Variables

DRCRegistration: Indicates whether the student is currently registered with the DRC.

- *Choices:* Yes No, and I don't think I should be registered No, but I should be registered

DRCWillingness: Indicates whether the student is willing to register with the DRC if eligible.

- *Choices:* Yes, No

CurrentAge: The student's current age.

ResidenceType: The type of area where the student resides.

- *Choices:* Urban, Suburban, Rural

USGrownUpStatus: Indicates whether the student grew up in the United States.

InternationalGrownUpStatus: Indicates whether the student grew up outside of the United States.

HouseholdIncome: The student's household income level.

- *Choices:* \$0–\$30,000, \$30,001–\$48,000, \$48,001–\$75,000, \$75,001–\$110,000, \$110,001+

WorkHours: The number of hours the student works per week while attending school.

- *Choices:* I do not work outside of doing my classwork., At least 5 hours, but less than 10 hours., 10–15 hours, 15–20 hours, 20 or more hours

ParentEducation: The highest level of education attained by the student's parent(s).

- *Choices:* Did not finish high school, High school diploma, Some college, Bachelor's degree, Graduate or professional degree

Race: The race or ethnicity with which the student identifies.

- *Choices:* White, Black or African American, Asian, Latino or Hispanic, Other

Sex: The student's biological sex.

- *Choices:* Male, Female, Prefer not to say, Other

LGBTQAStatus: Whether the student identifies as part of the LGBTQA community.

- *Choices:* Yes, No, Prefer not to say

Test and Quiz Grades

Test1Grade: The student's score on the first exam in the course.

Test2Grade: The student's score on the second exam in the course.

Test3Grade: The student's score on the third exam in the course.

Test4Grade: The student's score on the fourth exam in the course.

Quiz1Grade: The student's score on the first quiz in the course.

Quiz2Grade: The student's score on the second quiz in the course.

Quiz3Grade: The student's score on the third quiz in the course.

Quiz4Grade: The student's score on the fourth quiz in the course.

APPENDIX B: R CODE

```
#####  
#                                                                    #  
#                                                                    #  
#                               Load the data into R                               #  
#                                                                    #  
#                                                                    #  
#####  
  
#####  
#                                                                    #  
#                                                                    #  
#                               Load the data into R                               #  
#                                                                    #  
#                                                                    #  
#####  
  
#####  
# The here() package makes code much more portable by avoiding absolute paths.  #  
#####
```

```

library(here)

survey <- read.csv(here("survey.csv"), fileEncoding = "UTF-8", header = TRUE)

#####

#
#
#
#
#
#
#####

#####

# Load packages for data manipulation. #

#####

library(dplyr)

library(stringr)

#####

# Rename the variables in a sensible manner. #

#####

# Get the column names.

```

```
colnames(survey)

# Delete unnecessary columns.

survey$Q5<- NULL
survey$Q44_4_TEXT <- NULL
survey$Q6 <- NULL
survey$Q <- NULL
survey$Q7 <- NULL
survey$Q12_1 <- NULL
survey$Q12_2 <- NULL
survey$Q12_3 <- NULL
survey$Q12_4 <- NULL
survey$Q12_5 <- NULL
survey$Q9 <- NULL
survey$Q19_1 <- NULL
survey$Q19_2 <- NULL
survey$Q21 <- NULL
survey$Q23 <- NULL
survey$Q30 <- NULL
survey$Q31 <- NULL
survey$Q32 <- NULL
survey$Q35 <- NULL
survey$Q36 <- NULL
survey$Q37<- NULL
survey$Q39 <- NULL
```

```

survey$Q41_7_TEXT <- NULL
survey$Q42_4_TEXT <- NULL
survey$Q44 <- NULL
survey$Quiz_1_Grade <- NULL
survey$Quiz_2_Grade <- NULL
survey$Quiz_3_Grade <- NULL
survey$Quiz_4_Grade<- NULL
survey$Q5.1<- NULL
survey$Q5_9_TEXT<- NULL
survey$Q7.1<- NULL
survey$Q8_1<- NULL

```

```

# #####
# Rename the column names. ##
# #####

```

```

updated_survey <- survey %>%
  dplyr:: select(
    Q1,
    Q8_2,
    Q8_3,
    Q9_1,
    Q11,
    Q29,
    Q33,
    Q34,

```



```

Q38,
Q40,
Q41,
Q42,
Q43,
Q_44_4,
Test_1_.Grade,
Test_2_Grade,
Test_3_Grade,
Test_4_Grade
) %>%
rename(
  Participation = Q1,
  TransferStatus = Q9_1,
  ActiveLearningEnhancedUnderstandingComparedLecture = Q8_2,
  ComfortEngagingPeersInstructors = Q8_3,
  PeerEngagementPreferenceSTEM = Q11,
  DRCRegistration = Q29,
  CurrentAge = Q33,
  ResidenceType = Q34,
  HouseholdIncome = Q38,
  ParentEducation = Q40,
  Race = Q41,
  Sex = Q42,
  LGBTQIAStatus = Q43,
  Test1Grade = `Test_1_.Grade`,
  Test2Grade = Test_2_Grade,
  Test3Grade = Test_3_Grade,

```

```

Test4Grade = `Test_4_Grade`,
ActiveLearningSection = Q_44_4
)

```

```

# Drop the first two rows

```

```

updated_survey <- updated_survey[-c(1, 2), ]
rownames(updated_survey) <- NULL

```

```

# Only keep participants who agreed to participate

```

```

updated_survey <- updated_survey %>%
  filter(Participation == "Yes, I agree to participate in the study.")

```

```

# Eliminate straight students

```

```

updated_survey <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say"))

```

```

# Identify active learning sections and link sections to instructors

```

```

yes_ActiveLearningSection <- c("57291", "57324", "57327", "57329", "57330",
↪ "57332", "57333", "57337",

```

```

      "57345", "57347", "64852", "64855", "64856",
      ↪ "64857", "64858", "64881",
      "64882", "64884", "64885", "64886", "64904",
      ↪ "64905", "64906", "64907",
      "64909", "64911", "64914", "64916", "64917",
      ↪ "64918")

Powell <- c("57291", "57327", "57330", "57332", "57333", "64852", "64855", "64856",
  ↪ "64857", "64858",
      "64904", "64905", "64909", "57324", "57329", "57347", "64906", "64907")

Toeppen <- c("57296", "64863", "64870", "64873", "64861", "64864")
Balasubramaniam <- c("57337", "64881", "64885", "64882", "64884", "64886")
Guo <- c("64911", "64914", "64916", "64917", "64918", "57345")

updated_survey <- updated_survey %>%
  mutate(
    CRN = str_extract(ActiveLearningSection, "\\d{5}"),

    ActiveLearningSection = if_else(CRN %in% yes_ActiveLearningSection, "Yes",
      ↪ "No"),

    Instructor = case_when(
      CRN %in% Powell ~ "Powell",
      CRN %in% Toeppen ~ "Toeppen",
      CRN %in% Balasubramaniam ~ "Balasubramaniam",
      CRN %in% Guo ~ "Guo",
      TRUE ~ NA_character_

```

```

    )
  )

# We know Nick's section was the only traditional classroom section.

updated_survey <- updated_survey %>%

  mutate(

    CRN = if_else(is.na(CRN), "64863", CRN),

    Instructor = if_else(is.na(Instructor), "Toebben", Instructor)

  )

# Recode racial categories

updated_survey <- updated_survey %>%

  mutate(

    Race = case_when(

      str_detect(str_to_lower(Race), "white") ~ "White",

      str_detect(str_to_lower(Race), "black|african") ~ "Black or African
      ↪ American",

      str_detect(str_to_lower(Race), "asian") ~ "Asian",

      str_detect(str_to_lower(Race), "hispanic|latino") ~ "Hispanic or Latino",

      str_detect(str_to_lower(Race), "american indian|alaska native") ~ "American
      ↪ Indian or Alaska Native",

      str_detect(str_to_lower(Race), "native hawaiian|pacific islander") ~ "Native
      ↪ Hawaiian or Pacific Islander",

      TRUE ~ "Multiracial or Other"

    )

  )

```

```
# Recode Transfer Status
```

```
updated_survey <- updated_survey %>%  
  mutate(  
    TransferStatus = if_else(str_detect(TransferStatus, "did not"), "No", "Yes")  
  )
```

```
# Recode DRC Status
```

```
updated_survey <- updated_survey %>%  
  mutate(  
    DRCRegistration = if_else(  
      str_detect(DRCRegistration, "^No, and|^No, but|^Not Applicable"),  
      "No",  
      "Yes"  
    )  
  )
```

```
# Condense Household income values
```

```
updated_survey <- updated_survey %>%  
  mutate(  
    HouseholdIncome = str_replace(HouseholdIncome, "^More than", ">")  
  )
```

```
# Update sex category
```

```

updated_survey <- updated_survey %>%

  mutate(

    Sex = if_else(Sex == "Prefer not to say", "Other", Sex)

  )

#####
# To simplify our calculations, we add each students' test grades,
# so they are out of 400 points. #
#####

updated_survey <- updated_survey %>%

  mutate(

    Test1Grade = as.numeric(Test1Grade),
    Test2Grade = as.numeric(Test2Grade),
    Test3Grade = as.numeric(Test3Grade),
    Test4Grade = as.numeric(Test4Grade)

  )

updated_survey <- updated_survey %>%

  mutate(

    TotalTestGrade = Test1Grade + Test2Grade + Test3Grade + Test4Grade

  )

```

```
# The student who scored a 5/400 on exams should be removed from the data set.
```

```
updated_survey <- updated_survey %>%
```

```
  filter(TotalTestGrade != 5)
```

```
View(updated_survey)
```

```
# #####
```

```
# Total missing values ##
```

```
# #####
```

```
sum(is.na(updated_survey))
```

```
#####
```

```
# #
```

```
# #
```

```
# Exploratory Data Analysis #
```

```
# #
```

```
# #
```

```
#####
```

```

# #####

# Contingency table of LGBTQIAStatus vs. Classroom Type ##
# #####

table(updated_survey$LGBTQIAStatus, updated_survey$ActiveLearningSection)

#####

#
# Bar graphs for EDA #
#
#####

#####

# Load packages to create graphics and visualizations.

#####

library(ggplot2)
library(patchwork)

#####

# If active learning enhances learning #

#####

refined_data <- updated_survey %>%

  filter(

    !is.na(ActiveLearningEnhancedUnderstandingComparedLecture),

    LGBTQIAStatus %in% c("Yes", "Prefer not to say")

  ) %>%

```



```

mutate(
  Enhanced_Learning = factor(
    trimws(as.character(ActiveLearningEnhancedUnderstandingComparedLecture)),
    levels = c(
      "Strongly Disagree", "Somewhat disagree", "Neither agree nor disagree",
      "Somewhat agree", "Strongly agree"
    ),
    ordered = TRUE
  ),
  LGBTQIAStatus = trimws(as.character(LGBTQIAStatus))
) %>%
group_by(LGBTQIAStatus, Enhanced_Learning) %>%
summarise(count = n(), .groups = "drop") %>%
group_by(LGBTQIAStatus) %>%
mutate(proportion = count / sum(count) * 100)

fill_colors <- c(
  "Strongly agree" = "#1b9e77",
  "Somewhat agree" = "#66c2a5",
  "Neither agree nor disagree" = "#e6ab02",
  "Somewhat disagree" = "#fc8d62",
  "Strongly Disagree" = "#d95f02"
)

plot1 <- ggplot(
  data = refined_data %>% filter(LGBTQIAStatus == "Yes"),
  aes(x = Enhanced_Learning, y = proportion, fill = Enhanced_Learning)
) +

```

```

geom_bar(stat = "identity") +
geom_text(aes(label = scales::percent(proportion / 100, accuracy = 0.1)),
          vjust = -0.1, size = 4) +
labs(
  title = "Active Learning Enhances Understanding for Openly LGBTQIA Students",
  x = "Agreement Level", y = "Proportion (%)"
) +
scale_fill_manual(values = fill_colors, drop = TRUE) +
theme_minimal() +
theme(
  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.title = element_text(hjust = 0.5, size = 14, margin = margin(b = 10)),
  legend.position = "none"
)

# Plot for undisclosed students
plot2 <- ggplot(
  data = refined_data %>% filter(LGBTQIAStatus == "Prefer not to say"),
  aes(x = Enhanced_Learning, y = proportion, fill = Enhanced_Learning)
) +
geom_bar(stat = "identity") +
geom_text(aes(label = scales::percent(proportion / 100, accuracy = 0.1)),
          vjust = -0.1, size = 4) +
labs(
  title = "Active Learning Enhances Understanding for Undisclosed Students",
  x = "Agreement Level", y = "Proportion (%)"
) +
scale_fill_manual(values = fill_colors, drop = TRUE) +

```

```

theme_minimal() +
theme(
  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.title = element_text(hjust = 0.5, size = 14, margin = margin(b = 10)),
  legend.position = "none"
)

final_plot <- plot1 / plot2 + plot_layout(nrow = 2)

final_plot

#####
# Comfort Engaging with Peers #
#####

refined_engagement <- updated_survey %>%
  filter(
    !is.na(ComfortEngagingPeersInstructors),
    LGBTQIAStatus %in% c("Yes", "Prefer not to say")
  ) %>%
  mutate(
    Engagement_Level = factor(
      trimws(as.character(ComfortEngagingPeersInstructors)),
      levels = c(
        "Strongly Disagree", "Somewhat disagree", "Neither agree nor disagree",
        "Somewhat agree", "Strongly agree"
      )
    )
  )

```

```

    ),
    ordered = TRUE
  ),
  LGBTQIAStatus = trimws(as.character(LGBTQIAStatus))
) %>%

group_by(LGBTQIAStatus, Engagement_Level) %>%
summarise(count = n(), .groups = "drop") %>%
group_by(LGBTQIAStatus) %>%
mutate(proportion = count / sum(count) * 100)

# Define consistent fill colors
fill_colors <- c(
  "Strongly agree" = "#1b9e77",
  "Somewhat agree" = "#66c2a5",
  "Neither agree nor disagree" = "#e6ab02",
  "Somewhat disagree" = "#fc8d62",
  "Strongly Disagree" = "#d95f02"
)

# Openly LGBTQIA students
plot1 <- ggplot(
  data = refined_engagement %>% filter(LGBTQIAStatus == "Yes"),
  aes(x = Engagement_Level, y = proportion, fill = Engagement_Level)
) +
  geom_bar(stat = "identity") +
  geom_text(
    aes(label = scales::percent(proportion / 100, accuracy = 0.1)),
    vjust = -0.1, size = 4
  )

```

```

) +
labs(
  title = "Comfort Engaging with Peers and Instructors for Openly LGBTQIA
  ↪ Students",
  x = "Agreement Level", y = "Proportion (%)"
) +
scale_fill_manual(values = fill_colors, drop = TRUE) +
theme_minimal() +
theme(
  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.title = element_text(hjust = 0.5, size = 14, margin = margin(t = 15, b =
  ↪ 10)),
  legend.position = "none"
)

# Undisclosed students
plot2 <- ggplot(
  data = refined_engagement %>% filter(LGBTQIAStatus == "Prefer not to say"),
  aes(x = Engagement_Level, y = proportion, fill = Engagement_Level)
) +
geom_bar(stat = "identity") +
geom_text(
  aes(label = scales::percent(proportion / 100, accuracy = 0.1)),
  vjust = -0.1, size = 4
) +
labs(
  title = "Comfort Engaging with Peers and Instructors for Undisclosed Students",
  x = "Agreement Level", y = "Proportion (%)"

```

```

) +
scale_fill_manual(values = fill_colors, drop = TRUE) +
theme_minimal() +
theme(
  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.title = element_text(hjust = 0.5, size = 14, margin = margin(t = 15, b =
↵ 10)),
  legend.position = "none"
)

final_plot <- plot1 / plot2 + plot_layout(nrow = 2)
final_plot

```

```

#####
# Desired Peer Engagement Frequency                                     #
#####

```

```

refined_peer_engagement <- updated_survey %>%
  filter(
    !is.na(PeerEngagementPreferenceSTEM),
    LGBTQIAStatus %in% c("Yes", "Prefer not to say")
  ) %>%
  mutate(
    Peer_Engagement = factor(
      trimws(as.character(PeerEngagementPreferenceSTEM)),

```

```

    levels = c("Never", "Once a week", "Once per class", "Multiple times each
    ↪ class"),
    ordered = TRUE
  ),
  LGBTQIAStatus = trimws(as.character(LGBTQIAStatus))
) %>%

group_by(LGBTQIAStatus, Peer_Engagement) %>%
summarise(count = n(), .groups = "drop") %>%
group_by(LGBTQIAStatus) %>%
mutate(proportion = count / sum(count) * 100)

engagement_colors <- c(
  "Never" = "#d73027",
  "Once a week" = "#fc8d62",
  "Once per class" = "#e6ab02",
  "Multiple times each class" = "#1b9e77"
)

# Openly LGBTQIA students
plot1 <- ggplot(
  data = refined_peer_engagement %>% filter(LGBTQIAStatus == "Yes"),
  aes(x = Peer_Engagement, y = proportion, fill = Peer_Engagement)
) +
  geom_bar(stat = "identity") +
  geom_text(
    aes(label = scales::percent(proportion / 100, accuracy = 0.1)),
    vjust = -0.1, size = 4
  ) +

```

```

labs(
  title = "Desired Peer Engagement Frequency for Openly LGBTQIA Students",
  x = "Engagement Frequency", y = "Proportion (%)"
) +
scale_fill_manual(values = engagement_colors, drop = TRUE) +
theme_minimal() +
theme(
  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.title = element_text(hjust = 0.5, size = 14, margin = margin(t = 15, b =
↵ 10)),
  legend.position = "none"
)

# Undisclosed students
plot2 <- ggplot(
  data = refined_peer_engagement %>% filter(LGBTQIAStatus == "Prefer not to say"),
  aes(x = Peer_Engagement, y = proportion, fill = Peer_Engagement)
) +
geom_bar(stat = "identity") +
geom_text(
  aes(label = scales::percent(proportion / 100, accuracy = 0.1)),
  vjust = -0.1, size = 4
) +
labs(
  title = "Desired Peer Engagement Frequency for Undisclosed Students",
  x = "Engagement Frequency", y = "Proportion (%)"
) +
scale_fill_manual(values = engagement_colors, drop = TRUE) +

```



```

theme_minimal() +
theme(
  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.title = element_text(hjust = 0.5, size = 14, margin = margin(t = 15, b =
↵ 10)),
  legend.position = "none"
)

final_plot <- plot1 / plot2 + plot_layout(nrow = 2)
final_plot

#####

#                                     #
#      Comparing students' test grades      #
#                                     #
#####

#####

# Test 1 grades #

#####

# Table

summary_stats <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  group_by(LGBTQIAStatus, ActiveLearningSection) %>%
  summarise(
    n = n(),

```

```

Mean_Test1 = round(mean(Test1Grade), 1),
SD_Test1 = round(sd(Test1Grade), 1),
Mean_Total = round(mean(TotalTestGrade), 1),
SD_Total = round(sd(TotalTestGrade), 1),
.groups = "drop"
)

summary_stats

row_totals <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  group_by(LGBTQIAStatus) %>%
  summarise(
    n = n(),
    Mean_Test1 = round(mean(Test1Grade), 1),
    SD_Test1 = round(sd(Test1Grade), 1),
    Mean_Total = round(mean(TotalTestGrade), 1),
    SD_Total = round(sd(TotalTestGrade), 1),
    .groups = "drop"
  )

row_totals

col_totals <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  group_by(ActiveLearningSection) %>%
  summarise(
    n = n(),

```

```

    Mean_Test1 = round(mean(Test1Grade), 1),
    SD_Test1 = round(sd(Test1Grade), 1),
    Mean_Total = round(mean(TotalTestGrade), 1),
    SD_Total = round(sd(TotalTestGrade), 1),
    .groups = "drop"
  )

col_totals

grand_total <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  summarise(
    n = n(),
    Mean_Test1 = round(mean(Test1Grade), 1),
    SD_Test1 = round(sd(Test1Grade), 1),
    Mean_Total = round(mean(TotalTestGrade), 1),
    SD_Total = round(sd(TotalTestGrade), 1)
  )

grand_total

# Boxplot

test1_data <- updated_survey %>%
  filter(
    LGBTQIAStatus %in% c("Yes", "Prefer not to say"),
    !is.na(Test1Grade),

```

```

    !is.na(ActiveLearningSection)
  ) %>%
mutate(
  ActiveLearningGroup = ActiveLearningSection,
  Percentage_Grade = round((Test1Grade / 100) * 100, 1)
)

test1_data_yes_LGBTQIA <- test1_data %>%
  filter(LGBTQIAStatus == "Yes")

test1_data_prefer_not_say <- test1_data %>%
  filter(LGBTQIAStatus == "Prefer not to say")

# Openly LGBTQIA Students
plot1 <- ggplot(test1_data_yes_LGBTQIA, aes(x = ActiveLearningGroup, y =
↪ Percentage_Grade, fill = ActiveLearningGroup)) +
  geom_boxplot(outlier.color = "red", outlier.size = 2) +
  labs(
    title = "Test 1 Grades of Openly LGBTQIA Students",
    x = "Class Utilized Active Learning Techniques",
    y = "Test 1 Grade (%)",
    fill = "Active Learning Group"
  ) +
  theme_minimal() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    plot.title = element_text(hjust = 0.5),
    legend.title = element_text(size = 12)
  )

```

```

) +

scale_fill_brewer(palette = "Set3")

# Undisclosed Students

plot2 <- ggplot(test1_data_prefer_not_say, aes(x = ActiveLearningGroup, y =
↪ Percentage_Grade, fill = ActiveLearningGroup)) +

geom_boxplot(outlier.color = "red", outlier.size = 2) +

labs(

  title = "Test 1 Grades of Undisclosed Students",
  x = "Class Utilized Active Learning Techniques",
  y = "Test 1 Grade (%)",
  fill = "Active Learning Group"
) +

theme_minimal() +

theme(

  axis.text.x = element_text(angle = 45, hjust = 1),
  plot.title = element_text(hjust = 0.5),
  legend.title = element_text(size = 12)
) +

scale_fill_brewer(palette = "Set3")

final_plot <- plot1 / plot2 + plot_layout(nrow = 2)
final_plot

# Check conditions

library(car)

```

```

# -----
# Shapiro-Wilk Test for Normality
# -----

# Openly LGBTQIA students
shapiro.test(
  test1_data_yes_LGBTQIA$Test1Grade[test1_data_yes_LGBTQIA$ActiveLearningGroup ==
    ↪ "Yes"]
)
shapiro.test(
  test1_data_yes_LGBTQIA$Test1Grade[test1_data_yes_LGBTQIA$ActiveLearningGroup ==
    ↪ "No"]
)

# Undisclosed students
shapiro.test(
  ↪ test1_data_prefer_not_say$Test1Grade[test1_data_prefer_not_say$ActiveLearningGroup
  ↪ == "Yes"]
)
shapiro.test(
  ↪ test1_data_prefer_not_say$Test1Grade[test1_data_prefer_not_say$ActiveLearningGroup
  ↪ == "No"]
)

# -----

```

```

# Levene's Test for Equal Variances
# -----

leveneTest(Test1Grade ~ ActiveLearningGroup, data = test1_data_yes_LGBTQIA)
leveneTest(Test1Grade ~ ActiveLearningGroup, data = test1_data_prefer_not_say)

# -----
# Two-Sample t-tests (equal variance assumed)
# -----

t.test(Test1Grade ~ ActiveLearningGroup,
       data = test1_data_yes_LGBTQIA,
       var.equal = TRUE)

t.test(Test1Grade ~ ActiveLearningGroup,
       data = test1_data_prefer_not_say,
       var.equal = TRUE)

#####
# Test 1 + Test 2 grades #
#####

# Table

summary_stats <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(
    CombinedTest12 = Test1Grade + Test2Grade

```

```

) %>%

group_by(LGBTQIAStatus, ActiveLearningSection) %>%

summarise(

  n = n(),

  Mean_Test12 = round(mean(CombinedTest12, na.rm = TRUE), 1),

  SD_Test12 = round(sd(CombinedTest12, na.rm = TRUE), 1),

  .groups = "drop"

)

```

summary_stats

```

row_totals <- updated_survey %>%

  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%

  mutate(CombinedTest12 = Test1Grade + Test2Grade) %>%

  group_by(LGBTQIAStatus) %>%

  summarise(

    n = n(),

    Mean_Test12 = round(mean(CombinedTest12, na.rm = TRUE), 1),

    SD_Test12 = round(sd(CombinedTest12, na.rm = TRUE), 1),

    .groups = "drop"

  ) %>%

  mutate(ActiveLearningSection = "Total")

```

row_totals

```

col_totals <- updated_survey %>%

  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%

  mutate(CombinedTest12 = Test1Grade + Test2Grade) %>%

```



```

group_by(ActiveLearningSection) %>%
summarise(
  n = n(),
  Mean_Test12 = round(mean(CombinedTest12, na.rm = TRUE), 1),
  SD_Test12 = round(sd(CombinedTest12, na.rm = TRUE), 1),
  .groups = "drop"
) %>%
mutate(LGBTQIAStatus = "Total")

```

col_totals

```

grand_total <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(CombinedTest12 = Test1Grade + Test2Grade) %>%
  summarise(
    n = n(),
    Mean_Test12 = round(mean(CombinedTest12, na.rm = TRUE), 1),
    SD_Test12 = round(sd(CombinedTest12, na.rm = TRUE), 1)
  ) %>%
  mutate(
    LGBTQIAStatus = "Total",
    ActiveLearningSection = "Total"
  )

```

grand_total

Boxplots

```

test12_data <- updated_survey %>%
  filter(
    LGBTQIAStatus %in% c("Yes", "Prefer not to say"),
    !is.na(Test1Grade), !is.na(Test2Grade),
    !is.na(ActiveLearningSection)
  ) %>%
  mutate(
    ActiveLearningGroup = ActiveLearningSection,
    CombinedTest12 = Test1Grade + Test2Grade,
    Percentage_Grade = round((CombinedTest12 / 200) * 100, 1)
  )

test12_data_yes <- test12_data %>%
  filter(LGBTQIAStatus == "Yes")

test12_data_otsay <- test12_data %>%
  filter(LGBTQIAStatus == "Prefer not to say")

# Openly LGBTQIA Students
plot1 <- ggplot(test12_data_yes, aes(x = ActiveLearningGroup, y = Percentage_Grade,
  ↪ fill = ActiveLearningGroup)) +
  geom_boxplot(outlier.color = "red", outlier.size = 2) +
  labs(
    title = "Test 1 + 2 Grades of Openly LGBTQIA Students",
    x = "Class Utilized Active Learning Techniques",
    y = "Combined Grade (%)",
    fill = "Active Learning Group"
  )

```

```

) +

theme_minimal() +

theme(axis.text.x = element_text(angle = 45, hjust = 1)) +

scale_fill_brewer(palette = "Set3")

# Prefer Not to Say

plot2 <- ggplot(test12_data_otsay, aes(x = ActiveLearningGroup, y =
↪ Percentage_Grade, fill = ActiveLearningGroup)) +

geom_boxplot(outlier.color = "red", outlier.size = 2) +

labs(

  title = "Test 1 + 2 Grades of Undisclosed Students",

  x = "Class Utilized Active Learning Techniques",

  y = "Combined Grade (%)",

  fill = "Active Learning Group"

) +

theme_minimal() +

theme(axis.text.x = element_text(angle = 45, hjust = 1)) +

scale_fill_brewer(palette = "Set3")

final_plot <- plot1 / plot2 + patchwork::plot_layout(nrow = 2)

final_plot

# Check conditions

# Shapiro-Wilk Tests

shapiro.test(test12_data_yes$CombinedTest12[test12_data_yes$ActiveLearningGroup ==
↪ "Yes"])
```

```

shapiro.test(test12_data_yes$CombinedTest12[test12_data_yes$ActiveLearningGroup ==
↳ "No"])

shapiro.test(test12_data_notsay$CombinedTest12[test12_data_notsay$ActiveLearningGroup
↳ == "Yes"])

shapiro.test(test12_data_notsay$CombinedTest12[test12_data_notsay$ActiveLearningGroup
↳ == "No"])

# Levene's Test
leveneTest(CombinedTest12 ~ ActiveLearningGroup, data = test12_data_yes)
leveneTest(CombinedTest12 ~ ActiveLearningGroup, data = test12_data_notsay)

# Two-sample t-tests (equal variance)
t.test(CombinedTest12 ~ ActiveLearningGroup, data = test12_data_yes, var.equal =
↳ TRUE)
t.test(CombinedTest12 ~ ActiveLearningGroup, data = test12_data_notsay, var.equal =
↳ TRUE)

#####
# Test 1 + Test 2 + Test 3 grades #
#####

# Tables

summary_stats <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(

```

```

    CombinedTest123 = Test1Grade + Test2Grade + Test3Grade
  ) %>%
  group_by(LGBTQIAStatus, ActiveLearningSection) %>%
  summarise(
    n = n(),
    Mean_Test123 = round(mean(CombinedTest123, na.rm = TRUE), 1),
    SD_Test123 = round(sd(CombinedTest123, na.rm = TRUE), 1),
    .groups = "drop"
  )

summary_stats

row_totals <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(CombinedTest123 = Test1Grade + Test2Grade + Test3Grade) %>%
  group_by(LGBTQIAStatus) %>%
  summarise(
    n = n(),
    Mean_Test123 = round(mean(CombinedTest123, na.rm = TRUE), 1),
    SD_Test123 = round(sd(CombinedTest123, na.rm = TRUE), 1),
    .groups = "drop"
  ) %>%
  mutate(ActiveLearningSection = "Total")

row_totals

col_totals <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%

```

```

mutate(CombinedTest123 = Test1Grade + Test2Grade + Test3Grade) %>%
group_by(ActiveLearningSection) %>%
summarise(
  n = n(),
  Mean_Test123 = round(mean(CombinedTest123, na.rm = TRUE), 1),
  SD_Test123 = round(sd(CombinedTest123, na.rm = TRUE), 1),
  .groups = "drop"
) %>%
mutate(LGBTQIAStatus = "Total")

col_totals

grand_total <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(CombinedTest123 = Test1Grade + Test2Grade + Test3Grade) %>%
  summarise(
    n = n(),
    Mean_Test123 = round(mean(CombinedTest123, na.rm = TRUE), 1),
    SD_Test123 = round(sd(CombinedTest123, na.rm = TRUE), 1)
  ) %>%
  mutate(
    LGBTQIAStatus = "Total",
    ActiveLearningSection = "Total"
  )

grand_total

# Boxplots

```

```

test123_data <- updated_survey %>%
  filter(
    LGBTQIAStatus %in% c("Yes", "Prefer not to say"),
    !is.na(Test1Grade), !is.na(Test2Grade), !is.na(Test3Grade),
    !is.na(ActiveLearningSection)
  ) %>%
  mutate(
    ActiveLearningGroup = ActiveLearningSection,
    CombinedTest123 = Test1Grade + Test2Grade + Test3Grade,
    Percentage_Grade = round((CombinedTest123 / 300) * 100, 1)
  )

test123_data_yes <- test123_data %>%
  filter(LGBTQIAStatus == "Yes")

test123_data_notsay <- test123_data %>%
  filter(LGBTQIAStatus == "Prefer not to say")

# Openly LGBTQIA Students
plot1 <- ggplot(test123_data_yes, aes(x = ActiveLearningGroup, y =
  ↪ Percentage_Grade, fill = ActiveLearningGroup)) +
  geom_boxplot(outlier.color = "red", outlier.size = 2) +
  labs(
    title = "Test 1 + 2 + 3 Grades of Openly LGBTQIA Students",
    x = "Class Utilized Active Learning Techniques",
    y = "Combined Grade (%)",
    fill = "Active Learning Group"
  )

```

```

) +

theme_minimal() +

theme(axis.text.x = element_text(angle = 45, hjust = 1)) +

scale_fill_brewer(palette = "Set3")

# Prefer Not to Say

plot2 <- ggplot(test123_data_notsay, aes(x = ActiveLearningGroup, y =
↪ Percentage_Grade, fill = ActiveLearningGroup)) +

geom_boxplot(outlier.color = "red", outlier.size = 2) +

labs(

  title = "Test 1 + 2 + 3 Grades of Undisclosed Students",

  x = "Class Utilized Active Learning Techniques",

  y = "Combined Grade (%)",

  fill = "Active Learning Group"

) +

theme_minimal() +

theme(axis.text.x = element_text(angle = 45, hjust = 1)) +

scale_fill_brewer(palette = "Set3")

final_plot <- plot1 / plot2 + patchwork::plot_layout(nrow = 2)

final_plot

# Check conditions

# Shapiro-Wilk Tests

shapiro.test(test123_data_yes$CombinedTest123[test123_data_yes$ActiveLearningGroup
↪ == "Yes"])

```



```

shapiro.test(test123_data_yes$CombinedTest123[test123_data_yes$ActiveLearningGroup
↪ == "No"])

shapiro.test(test123_data_notsay$CombinedTest123[test123_data_notsay$ActiveLearningGroup
↪ == "Yes"])

shapiro.test(test123_data_notsay$CombinedTest123[test123_data_notsay$ActiveLearningGroup
↪ == "No"])

# Levene's Test
leveneTest(CombinedTest123 ~ ActiveLearningGroup, data = test123_data_yes)
leveneTest(CombinedTest123 ~ ActiveLearningGroup, data = test123_data_notsay)

# Two-sample t-tests (equal variance)
t.test(CombinedTest123 ~ ActiveLearningGroup, data = test123_data_yes, var.equal =
↪ TRUE)
t.test(CombinedTest123 ~ ActiveLearningGroup, data = test123_data_notsay, var.equal
↪ = TRUE)

#####
# Test 1 + Test 2 + Test 4 grades #
#####

# Table

summary_stats <- updated_survey %>%

```

```

filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
mutate(
  CombinedTest1234 = Test1Grade + Test2Grade + Test3Grade + Test4Grade
) %>%
group_by(LGBTQIAStatus, ActiveLearningSection) %>%
summarise(
  n = n(),
  Mean_Test1234 = round(mean(CombinedTest1234, na.rm = TRUE), 1),
  SD_Test1234 = round(sd(CombinedTest1234, na.rm = TRUE), 1),
  .groups = "drop"
)

summary_stats

row_totals <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(CombinedTest1234 = Test1Grade + Test2Grade + Test3Grade + Test4Grade) %>%
  group_by(LGBTQIAStatus) %>%
  summarise(
    n = n(),
    Mean_Test1234 = round(mean(CombinedTest1234, na.rm = TRUE), 1),
    SD_Test1234 = round(sd(CombinedTest1234, na.rm = TRUE), 1),
    .groups = "drop"
  ) %>%
  mutate(ActiveLearningSection = "Total")

row_totals

```

```
col_totals <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(CombinedTest1234 = Test1Grade + Test2Grade + Test3Grade + Test4Grade) %>%
  group_by(ActiveLearningSection) %>%
  summarise(
    n = n(),
    Mean_Test1234 = round(mean(CombinedTest1234, na.rm = TRUE), 1),
    SD_Test1234 = round(sd(CombinedTest1234, na.rm = TRUE), 1),
    .groups = "drop"
  ) %>%
  mutate(LGBTQIAStatus = "Total")

col_totals
```

```
grand_total <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(CombinedTest1234 = Test1Grade + Test2Grade + Test3Grade + Test4Grade) %>%
  summarise(
    n = n(),
    Mean_Test1234 = round(mean(CombinedTest1234, na.rm = TRUE), 1),
    SD_Test1234 = round(sd(CombinedTest1234, na.rm = TRUE), 1)
  ) %>%
  mutate(
    LGBTQIAStatus = "Total",
    ActiveLearningSection = "Total"
  )

grand_total
```

```
# Boxplots
```

```
test1234_data <- updated_survey %>%  
  filter(  
    LGBTQIAStatus %in% c("Yes", "Prefer not to say"),  
    !is.na(Test1Grade), !is.na(Test2Grade), !is.na(Test3Grade), !is.na(Test4Grade),  
    !is.na(ActiveLearningSection)  
  ) %>%  
  mutate(  
    ActiveLearningGroup = ActiveLearningSection,  
    CombinedTest1234 = Test1Grade + Test2Grade + Test3Grade + Test4Grade,  
    Percentage_Grade = round((CombinedTest1234 / 400) * 100, 1)  
  )
```

```
test1234_data_yes <- test1234_data %>%  
  filter(LGBTQIAStatus == "Yes")
```

```
test1234_data_notsay <- test1234_data %>%  
  filter(LGBTQIAStatus == "Prefer not to say")
```

```
# Openly LGBTQIA Students
```

```
plot1 <- ggplot(test1234_data_yes, aes(x = ActiveLearningGroup, y =  
  ↪ Percentage_Grade, fill = ActiveLearningGroup)) +  
  geom_boxplot(outlier.color = "red", outlier.size = 2) +  
  labs(  
    title = "Percentage Grade by Active Learning Group (Openly LGBTQIA Students)",  
    xlab = "Active Learning Group",  
    ylab = "Percentage Grade",  
    theme_minimal()
```

```

    title = "Test 1-4 Grades of Openly LGBTQIA Students",
    x = "Class Utilized Active Learning Techniques",
    y = "Combined Grade (%)",
    fill = "Active Learning Group"
) +

theme_minimal() +

theme(axis.text.x = element_text(angle = 45, hjust = 1)) +

scale_fill_brewer(palette = "Set3")

# Undisclosed Students

plot2 <- ggplot(test1234_data_notsay, aes(x = ActiveLearningGroup, y =
↪ Percentage_Grade, fill = ActiveLearningGroup)) +

geom_boxplot(outlier.color = "red", outlier.size = 2) +

labs(

    title = "Test 1-4 Grades of Undisclosed Students",
    x = "Class Utilized Active Learning Techniques",
    y = "Combined Grade (%)",
    fill = "Active Learning Group"
) +

theme_minimal() +

theme(axis.text.x = element_text(angle = 45, hjust = 1)) +

scale_fill_brewer(palette = "Set3")

final_plot <- plot1 / plot2 + patchwork::plot_layout(nrow = 2)

final_plot

# Conditions

```

```

# Shapiro-Wilk Tests

shapiro.test(test1234_data_yes$CombinedTest1234[test1234_data_yes$ActiveLearningGroup
↪ == "Yes"])

shapiro.test(test1234_data_yes$CombinedTest1234[test1234_data_yes$ActiveLearningGroup
↪ == "No"])

shapiro.test(test1234_data_notsay$CombinedTest1234[test1234_data_notsay$ActiveLearningGroup
↪ == "Yes"])

shapiro.test(test1234_data_notsay$CombinedTest1234[test1234_data_notsay$ActiveLearningGroup
↪ == "No"])

# Levene's Test

leveneTest(CombinedTest1234 ~ ActiveLearningGroup, data = test1234_data_yes)

leveneTest(CombinedTest1234 ~ ActiveLearningGroup, data = test1234_data_notsay)

# Two-sample t-tests (equal variance)

t.test(CombinedTest1234 ~ ActiveLearningGroup, data = test1234_data_yes, var.equal
↪ = TRUE)

t.test(CombinedTest1234 ~ ActiveLearningGroup, data = test1234_data_notsay,
↪ var.equal = TRUE)

#####

# #

# #

# Methods #

# #

# #

#####

```

```
#####

# Step 1: Multiple Regression #

#####

# -----

# Import the MASS package

# -----

library(MASS)

# -----

# Make sure the categorical
# variables are factors

# -----

updated_survey <- updated_survey %>%

  mutate(

    ActiveLearningSection = factor(ActiveLearningSection),

    LGBTQIAStatus = factor(LGBTQIAStatus),

    Race = factor(Race),

    Sex = factor(Sex),

    DRCRegistration = factor(DRCRegistration),

    TransferStatus = factor(TransferStatus),

    ParentEducation = factor(ParentEducation),

    ResidenceType = factor(ResidenceType),

    Instructor = factor(Instructor),
```

```

    HouseholdIncome = factor(HouseholdIncome)
  )

# Make sure Age is continuous

updated_survey <- updated_survey %>%
  mutate(CurrentAge = as.numeric(as.character(CurrentAge)))

# -----
# Openly LGBTQIA students
# -----

open <- updated_survey %>%
  filter(LGBTQIAStatus == "Yes") %>%
  mutate(
    ActiveLearningSection = factor(ActiveLearningSection),
    Race = factor(Race),
    Sex = factor(Sex),
    DRCRegistration = factor(DRCRegistration),
    TransferStatus = factor(TransferStatus),
    ParentEducation = factor(ParentEducation),
    ResidenceType = factor(ResidenceType),
    HouseholdIncome = factor(HouseholdIncome)
  )

# Count how many are in each level

```



```

table(open$ActiveLearningSection)
table(open$HouseholdIncome)
table(open$TransferStatus)
table(open$Sex)
table(open$DRCRegistration)

# Reset Baseline

open<- open %>%
  mutate(
    ActiveLearningSection = relevel(ActiveLearningSection, ref = "Yes"),
    HouseholdIncome = relevel(HouseholdIncome, ref = "> $110,000"),
    TransferStatus = relevel(TransferStatus, ref = "No"),
    Sex = relevel(Sex, ref = "Female"),
    DRCRegistration = relevel(DRCRegistration, ref = "No")
  )

# Fit multiple linear regression model
model_open <- lm(TotalTestGrade ~ ActiveLearningSection + HouseholdIncome +
  ↪ TransferStatus + CurrentAge +
    Sex + DRCRegistration,
    data = open)

summary(model_open)

AIC(model_open)
Anova(model_open)

```

```

par(mfrow = c(2, 2))
plot(model_open)
par(mfrow = c(1, 1))

shapiro.test(residuals(model_open))

vif(model_open)

# -----
# Prefer not to say students
# -----

notsay <- updated_survey %>%
  filter(LGBTQIAStatus == "Prefer not to say") %>%
  mutate(
    ActiveLearningSection = factor(ActiveLearningSection),
    Race = factor(Race),
    Sex = factor(Sex),
    DRCRegistration = factor(DRCRegistration),
    TransferStatus = factor(TransferStatus),
    ParentEducation = factor(ParentEducation),
    ResidenceType = factor(ResidenceType),
    HouseholdIncome = factor(HouseholdIncome)
  )

# Make sure Age is continuous

```

```

updated_survey <- updated_survey %>%
  mutate(CurrentAge = as.numeric(as.character(CurrentAge)))

# Number of observations in each level
table(notsay$ActiveLearningSection)
table(notsay$HouseholdIncome)
table(notsay$ResidenceType)
table(notsay$Race)
table(notsay$DRCRegistration)

# Reset Baseline

notsay <- notsay %>%
  mutate(
    ActiveLearningSection = relevel(ActiveLearningSection, ref = "Yes"),
    HouseholdIncome = relevel(HouseholdIncome, ref = "$48,001 - $75,000"),
    ResidenceType = relevel(ResidenceType, ref = "Suburban"),
    Race = relevel(Race, ref = "White"),
    DRCRegistration = relevel(DRCRegistration, ref = "No")
  )

# Fit multiple linear regression model

```

```
model_notsay <- lm(TotalTestGrade ~ ActiveLearningSection + HouseholdIncome +
  ↪ ResidenceType + Race + DRCRegistration,
  data = notsay)
```

```
summary(model_notsay)
```

```
AIC(model_notsay)
```

```
Anova(model_notsay)
```

```
par(mfrow = c(2, 2))
```

```
plot(model_notsay)
```

```
par(mfrow = c(1, 1))
```

```
shapiro.test(residuals(model_notsay))
```

```
vif(model_notsay)
```

```
# -----
```

```
# Both Groups
```

```
# -----
```

```
both <- updated_survey %>%
```

```
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
```

```
  mutate(
```

```

ActiveLearningSection = factor(ActiveLearningSection),
LGBTQIAStatus = factor(LGBTQIAStatus),
Race = factor(Race),
Sex = factor(Sex),
DRCRegistration = factor(DRCRegistration),
TransferStatus = factor(TransferStatus),
ParentEducation = factor(ParentEducation),
ResidenceType = factor(ResidenceType),
Instructor = factor(Instructor),
HouseholdIncome = factor(HouseholdIncome),
CurrentAge = as.numeric(as.character(CurrentAge))
)

# Number of observations in each level
table(both$ActiveLearningSection)
table(both$HouseholdIncome)
table(both$Race)
table(both$TransferStatus)
table(both$Sex)
table(both$DRCRegistration)

# Reset Baseline

both <- both %>%
  mutate(
    ActiveLearningSection = relevel(ActiveLearningSection, ref = "Yes"),
    HouseholdIncome = relevel(HouseholdIncome, ref = "> $110,000"),
    Race = relevel(Race, ref = "White"),

```

```

TransferStatus = relevel(TransferStatus, ref = "No"),
Sex = relevel(Sex, ref = "Female"),
DRCRegistration = relevel(DRCRegistration, ref = "No")
)

# Fit model
model_both <- lm(
  TotalTestGrade ~ ActiveLearningSection + HouseholdIncome + Race +
  TransferStatus + CurrentAge + Sex + DRCRegistration,
  data = both
)

summary(model_both)

AIC(model_both)
Anova(model_both)

par(mfrow = c(2, 2))
plot(model_both)
par(mfrow = c(1, 1))

shapiro.test(residuals(model_both))

vif(model_both)

#####

```

```

# Step 2: Multinomial Logistic Regression #

#####

# Load nnet library for multinomial logistic regression

library(nnet)

multi <- updated_survey %>%

  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%

  mutate(

    ActiveLearningSection = relevel(factor(ActiveLearningSection), ref = "Yes"),
    LGBTQIAStatus = factor(LGBTQIAStatus),
    Race = relevel(factor(Race), ref = "White"),
    Sex = relevel(factor(Sex), ref = "Female"),
    DRCRegistration = relevel(factor(DRCRegistration), ref = "No"),
    TransferStatus = relevel(factor(TransferStatus), ref = "No"),
    ParentEducation = relevel(factor(ParentEducation), ref = "Yes"),
    ResidenceType = relevel(factor(ResidenceType), ref = "Suburban"),
    Instructor = factor(Instructor),
    HouseholdIncome = relevel(factor(HouseholdIncome), ref = "> $110,000"),
    CurrentAge = as.numeric(as.character(CurrentAge)),
    PerformanceCategory = cut(
      100 * as.numeric(TotalTestGrade) / 400,
      breaks = c(0, 72.5, 82.3, 100),
      labels = c("Low", "Medium", "High"),
      include.lowest = TRUE,
      right = TRUE
    )
  )

```

)

```
multi_model <- multinom( PerformanceCategory ~ ActiveLearningSection +  
                          HouseholdIncome + ParentEducation + Race +  
                          TransferStatus + DRCRegistration,  
                          data = multi)
```

```
summary(multi_model)
```

```
# z-scores
```

```
summary_model <- summary(multi_model)  
z2 <- summary_model$coefficients / summary_model$standard.errors  
p2 <- 2 * (1 - pnorm(abs(z2))) # p-values
```

```
p2
```

```
# Odds ratios
```

```
odds_ratios <- exp(coef(multi_model))  
  
ci_lower <- summary_model$coefficients - 1.96 * summary_model$standard.errors  
ci_upper <- summary_model$coefficients + 1.96 * summary_model$standard.errors  
  
or_lower <- exp(ci_lower)  
or_upper <- exp(ci_upper)
```

```
or_table <- data.frame(
```



```

    Estimate = round(odds_ratios, 3),
    CI_Lower = round(or_lower, 3),
    CI_Upper = round(or_upper, 3)
)

print(or_table)

# Type II ANOVA
Anova(multi_model, type = "II")

#####

# Step 3: Mixed Models #

#####

# -----
# Import necessary packages
# -----

library(lme4)
library(sjPlot)

# -----
# Random Intercept
# -----

```

```

mixed_data <- updated_survey %>%

  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%

  mutate(

    ActiveLearningSection = factor(ActiveLearningSection),

    HouseholdIncome = factor(HouseholdIncome),

    Race = factor(Race),

    TransferStatus = factor(TransferStatus),

    DRCRegistration = factor(DRCRegistration),

    Sex = factor(Sex),

    Instructor = factor(Instructor),

    CurrentAge = as.numeric(as.character(CurrentAge))

  )

# Reset baseline

mixed_data <- mixed_data %>%

  mutate(

    ActiveLearningSection = relevel(ActiveLearningSection, ref = "Yes"),

    Race = relevel(Race, ref = "White"),

    Sex = relevel(Sex, ref = "Female"),

    DRCRegistration = relevel(DRCRegistration, ref = "No"),

    ResidenceType = relevel(ResidenceType, ref = "Suburban")

  )

# Fit Model

model_random_intercept <- lmer(

  TotalTestGrade ~ ActiveLearningSection + Race + Sex +

```

```

    CurrentAge + ResidenceType + DCRRegistration +
    (1 | Instructor),
  data = mixed_data
)

plot_model(
  model_random_intercept,
  type = "est",
  show.values = TRUE,
  show.p = TRUE,
  value.offset = 0.4,
  title = "Total Test Grade",
  dot.size = 2
)

# -----
# Random Slope
# -----

mixed_data <- updated_survey %>%
  filter(LGBTQIAStatus %in% c("Yes", "Prefer not to say")) %>%
  mutate(
    ActiveLearningSection = factor(ActiveLearningSection),
    HouseholdIncome = factor(HouseholdIncome),
    Race = factor(Race),
    TransferStatus = factor(TransferStatus),

```

```

DRCRegistration = factor(DRCRegistration),
Sex = factor(Sex),
ResidenceType = factor(ResidenceType),
Instructor = factor(Instructor),
CurrentAge = as.numeric(as.character(CurrentAge))
)

# Reset baseline

mixed_data <- mixed_data %>%
  mutate(
    ActiveLearningSection = relevel(ActiveLearningSection, ref = "Yes"),
    Race = relevel(Race, ref = "White"),
    Sex = relevel(Sex, ref = "Female"),
    ResidenceType = relevel(ResidenceType, ref = "Suburban"),
    DRCRegistration = relevel(DRCRegistration, ref = "No")
  )

# Fit model

model_random_slope <- lmer(
  TotalTestGrade ~ ActiveLearningSection + Race + Sex + ResidenceType +
    ↪ DRCRegistration +
    (0 + CurrentAge | Instructor),
  data = mixed_data
)

```

```

plot_model(
  model_random_slope,
  type = "est",
  show.values = TRUE,
  show.p = TRUE,
  value.offset = 0.4,
  title = "Total Test Grade",
  dot.size = 2
)

# -----
# Random Slope + Intercept
# -----

model_random_slope_intercept <- lmer(
  TotalTestGrade ~ ActiveLearningSection + Race + Sex + ResidenceType +
    DRCRegistration + CurrentAge + (CurrentAge | Instructor),
  data = mixed_data
)

summary(model_random_slope_intercept)

```